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Abstract

This study jointly examines agents' time dependence—period effects within instantaneous utility—and time preference—behavior on discounting future utility. The study considers the start- and end-of-period effects for time dependence and exponential and hyperbolic discounting for time preference. It provides identification arguments and sufficient conditions for both time constructs. The data include agents' work-shift schedules and daily observations in response to a firm's non-linear compensation structure, in which the final payment depends on the history of performance. By illustrating how various time constructs jointly affect behavior, the study provides implications for designing compensation structure and employee-shift scheduling. Specifically, it disentangles the effects of time constructs to examine the effectiveness of long versus short quota-evaluation cycles, quota-bonus versus commission incentive schemes, and employee-shift scheduling. In addition, the study provides a field validation that compares post-analysis actual and counterfactual outcomes to validate the prediction accuracy of the model.

Keywords: time dependence, period effects, time preference, present bias, hyperbolic discounting, compensation, dynamic structural models, identification.

1. Introduction

Human behavior is dynamic by nature. In response to various financial incentives, agents exhibit forward-looking behavior to dynamically allocate their time and effort in an attempt to meet future goals. Over time, people evaluate how close they are to achieving the goal and, if they are close to the goal, exert additional effort, or are too far from it, may even give up. In so doing, individuals typically discount future payoffs—valuing immediate utility over delayed utility—in assessing the value of the anticipated reward. In addition, agents’ motivations may directly depend on specific points in time. For instance, some people are extra motivated during the start of a new month, while others procrastinate and wait before taking action. As such, the various assessments of time affect agents’ response to an organization’s management levers, such as compensation structure—e.g., quota-evaluation and bonus-payout cycles—and work allocation and scheduling. Hence, understanding agents’ time constructs are important for management, as a means to align their motivation and incentives with those of the organization.

Organizations in the U.S. spend more than \$800 billion a year on sales force management, \$200 billion of which is devoted solely to compensation (Zoltners et al. 2013). Moreover, around 95% of U.S. organizations use some form of dynamic incentives to motivate their sales force, typically in the form of quota-based commissions and bonuses (Joseph and Kalwani 1998). Despite such large and widespread spending to stimulate sales agents’ dynamic behavior, there is limited understanding of how different elements of their time assessment affect performance. For instance, are agents more motivated during the start-of-quota period or the end-of-quota period, or both? What type of agents are motivated during such time periods? How does this interact with their time discounting? Are agents present-biased in their view towards future payoffs and, if so, to what degree?

This study aims to explain how various elements of agents’ time assessment collectively influence their motivation and, thus, performance outcomes. The study provides a comprehensive treatment around agents’ time assessment, including (1) *time preference*: how individuals discount their future payoffs; and (2) *time dependence*: how agents’ temporal states directly influence their instantaneous utility. The behaviors on time assessment are then associated with various management levers, including temporal quota-evaluation cycles, compensation components, and employee work-shift scheduling.

Time (discounting) preference¹ refers to the degree to which immediate utility is favored over delayed utility. To understand how people discount their future payoffs, studies have mainly used two models of time preference: exponential and hyperbolic discounting. The exponential discounting model postulates that people discount their future payoffs at a fixed rate (Samuelson 1937; Dhami 2016), and, thus, the model implies time-consistent behavior. On the contrary, the hyperbolic discounting model, often referred to as the Beta-Delta preference, implies time-inconsistent behavior (Phelps and Pollak 1968; Laibson 1997). The model posits that people are short-term impatient and, thus, present-biased—i.e., they discount the future from the present more than they do for the same time interval in distant future periods.

The models of time preference, however, do not fully capture the behavioral elements associated with time. For example, on New Year’s Day, people become exceptionally enthusiastic to set and work on their resolutions. Time sometimes directly affects an agent’s instantaneous utility, thus influencing his or her behavior in certain periods. These points in time, referred to as temporal landmarks (Shum 1998; Dai et al. 2014), are calendar events or special occasions—e.g., the beginning of a new year or a new semester, a birthday, or an anniversary—that psychologically demarcate the passage of time and change motivational behavior. This study captures such behavior through time dependence—the period effects within an agent’s instantaneous utility—to demonstrate how the agent’s states associated with the start and the end of the quota-evaluation cycle affect his or her actions.

By demonstrating how sales agents’ time assessments—both time preference and dependence—influence behavior in conjunction with multiple management levers, this study offers guidance to organizations on the optimal design of sales management policies. Specifically, the study examines whether agents’ motivations are time-dependent and, if so, when and for how long. In addition, it explores ways in which agents discount future payoffs—either time-consistent or present-biased. To do so, the study presents sufficient conditions to separately identify both time dependence and preference using naturally-occurring data. Finally, the study examines the implications of agents’ time assessment for an organization’s shift scheduling and compensation structure, including temporal quota-evaluation cycles and multiple compensation components.

¹ The term “time preference,” in general, includes all time constructs that influence an agent’s decision. In this study, we use the term to specifically denote the agent’s preference over time discounting, which is consistent with the terminology used in the structural econometrics literature.

There are some challenges in modeling and identifying agents’ time assessment. First, individual-level data with periods granular enough to capture temporal changes in behavior are often difficult to obtain, as many organizations evaluate and report performance only at an aggregate level—e.g., monthly. Hence, existing studies have narrowed their focus to identifying a limited scope of time assessment—i.e., only time preference such as exponential discounting (Yao et al. 2012; Chung et al. 2014; Ishihara and Ching 2019) and hyperbolic discounting (Fang and Wang 2015; Abbring et al. 2018; Chung et al. 2021a). Second, a researcher cannot observe the agents’ effort in response to their time assessment. Rather, the researcher observes only the performance outcomes, which are likely correlated with the agents’ forward-looking allocation of effort and their time dependence. This requires a behavioral assumption about the link between a sales agent’s motives—e.g., how close the person is to achieving quota at the end of the period, or how a different time horizon influences the ease and flexibility of exerting effort—and his or her allocation of effort over time. Lastly, and relatedly, the agent’s unobserved effort decisions are likely a result of time preference in conjunction with time dependence. Because the effects of the two unobserved time-assessment constructs on effort are interrelated, a careful econometric analysis is necessary to disentangle and separately identify the two constructs.

To overcome these challenges, we collaborate with a major Swedish retail chain and formulate a structural model in response to various management practices, taking into account agents’ time assessment. Exploiting the granular daily panel data, the model embeds the key elements of agents’ time assessment—including time discounting, present bias, start-of-the-period and end-of-the-period effects. Overall, we seek to gain insights into ways in which shift scheduling and compensation structure jointly affect the performance of heterogeneous agents.

This study also provides an important methodological contribution to the literature by presenting a formal proof of the conditions under which both time preference and time dependence are separately identified. We first discuss the identification conditions of time preference in a hyperbolic discounting model—a more general structure than an exponential discounting model. We then consider identification of time dependence in a fully flexible setting in which instantaneous utility depends arbitrarily on time and examine the associated limitations and necessary restrictions. Finally, we discuss identification regarding the duration of agents’ time dependence.

Building on the identification results, the empirical application shows support for agents’ time preference and time dependence and reveals how agents are heterogeneous in their time assessment. High-type agents are forward-looking and time-dependent, strongly motivated at the start and the end

of a month, whereas low-type agents are myopic and show limited time dependence, exerting low effort throughout the month. Agents’ performance escalation towards the end of the month is a result of both time preference (i.e., proximity to the goal) and time dependence (i.e., end-of-period effect).

A series of counterfactual simulations shows ways in which performance changes with alternative quota-evaluation cycles, compensation schemes, and shift-scheduling policies. A short quota-evaluation cycle motivates myopic, low-performing agents by giving them more frequent new opportunities, whereas a long quota-evaluation cycle motivates forward-looking, high-performing agents by offering them a shot at a big reward. Notably, because a short quota-evaluation cycle prevents low performers from giving up and helps them exert consistent effort, it reduces the *sales variance* across agents and, thus, allows an organization to better forecast and manage its sales outcomes. In terms of compensation components, although a bonus scheme with an adequate quota improves overall outcomes, such enhanced performance may come at a cost—the variance in performance across agents increases, as low-type agents are more likely to give up under the bonus scheme. Lastly, an organization can improve performance outcomes by tailoring the shift schedule to its agents’ time assessment—allocating more labor hours for forward-looking agents during the early period and more hours for myopic agents during the later period.

A field validation that compares the actual sales performance—following real changes in compensation structure—with the simulated counterfactual outcomes demonstrates the accuracy and applicability of the model. Hence, this study’s model can provide a practical application for organizations to understand their sales agents’ time assessment and to design their sales management policies accordingly.

The remainder of this study is structured as follows: Section 2 summarizes the related literature. Section 3 describes the institutional settings and provides model-free evidence that facilitates the empirical analysis. Section 4 presents the modeling framework of an agent’s time assessment. Section 5 discusses the identification of the model. Section 6 describes the estimation procedure. Section 7 discusses the estimation results, counterfactual simulations, and field validation. Section 8 concludes.

2. Related Literature

This study on time dependence and preference contributes to several streams of research. First, it relates to the research on time discounting and intertemporal decision making. To capture people’s discounting behavior of future outcomes, the literature mainly postulates two models of time preference—exponential and hyperbolic discounting. The exponential, or geometric, discounting model assumes that people discount the future at a fixed rate over time (Samuelson, 1937; Dharami, 2016), representing

stationarity and time-consistency. In contrast, the hyperbolic discounting model, commonly referred to as the Beta-Delta time preference, posits that people discount the future from the present more than they do for the time intervals in distant future periods (Ainslie 1975; Ainslie and Herrnstein 1981; Thaler 1981; Loewenstein and Prelec 1992; Laibson 1997; O’Donoghue and Rabin 1999), implying present bias and time-inconsistent behavior.

It is typically the case that one cannot identify time preference using naturally-occurring data because most variables simultaneously affect contemporaneous and future utilities (Rust 1994). Thus, to identify time preference, one would need specific variables—exclusion restrictions—that affect only the agent’s future payoff but not his or her current payoff (Magnac and Thesmar 2002). Studies have used the concept of exclusion restrictions to identify time preference (Fang and Wang 2015; Abbring and Daljord 2020; Chung et al. 2021a). This study builds upon the literature and identifies the agent’s effort using variation in sales performance in response to his or her state. Under a nonlinear incentive contract, with the payoff occurring at the end of the month, the agent’s state (i.e., how close the agent is to meeting the quota) during the remainder of the month provides exclusion restrictions because it affects only the future payoff, but not the current-period payoff (Chung et al. 2014, 2021a).

This study contributes to the literature by expanding the scope of intertemporal decision making to include an agent’s time dependence. The model offers a comprehensive treatment of how agents evaluate and respond to different points in time. Subsequently, the study provides formal conditions under which the agent’s time preference and time dependence are separately identified. To the best of our knowledge, this study’s empirical application is one of the first to jointly examine and identify the two unique time constructs of time dependence and preference.

This study also relates to the strand of research on time dependence and goal-directed behavior. Although the aforementioned literature on time discounting captures some of the essentials of intertemporal decision making, research has shown that people do not treat time as continuous and fungible (Rajagopal and Rha 2009; Soman 2001). Hence, some research has sought to understand the nonlinear aspects of time, investigating the situational factors that observably motivate people beyond those explained by the Beta-Delta time preference (Thaler and Ganser 2015; Beshears et al. 2016). For instance, Beta-Delta preference is limited in capturing behaviors that entail up-front costs and delayed benefits because it posits that the past is *always* valued less than the future.

One example of such situational factors is the “fresh-start effect.” People perceive time as divided into chunks of weeks, months, or years that are separated by temporal boundaries (Peetz and Wilson

2013), and research has shown that people are more likely to engage in self-controlled acts at the start of new cycles, such as the beginning of the week, month, or year (Marlatt and Kaplan 1972; Norcross et al. 2002; Dai et al. 2014). The temporal boundaries, sometimes referred to as temporal landmarks, demarcate the passage of time and create separate mental accounting periods for organizing activities and plans (LeBoeuf et al. 2014; Peetz and Wilson 2013; Robinson 1986; Soster et al. 2010; Tu and Soman 2014). At the start of a new cycle, people perceive their previous underachievement as having occurred in a more distant past, and this psychological distance creates an opportunity to take on optimistic actions and new goals (Bandura 1997; Dai et al. 2015).

Just as the fresh-start effect may provide support for people’s motivation at the beginning of a period, the goal-gradient hypothesis (Hull 1932, 1938) may support their motivation towards the end of a period. As people approach the end of a goal pursuit, their marginal valuation of the reward increases (i.e., the goal gradient becomes steeper) because the time interval between the present and the goal, which serves as a reference point, becomes shorter. Consequently, people become better motivated as their progress nears the end of the period (Cheema and Bagchi 2011; Kivetz et al. 2006; Nunes and Drèze 2006). Actions at the beginning and end of a period are more salient, and, as such, people adhere to their goal pursuit more closely during these periods (Touré-Tillery and Fishbach 2011).

This study’s contribution to the stream of literature on time dependence is threefold. First, it empirically verifies time dependence using naturally-occurring data. Because people’s time-dependent behavior is unobserved, academics have relied mainly on lab- or survey-based experiments, both of which focus on imaginary responses. By identifying time dependence based on actual, rather than imaginary, choices in a real-work environment, the study advances the literature in finding the true behavioral motives created by temporal boundaries. Second, the study not only demonstrates the existence (or the lack) of time dependence, but it also identifies the duration of such dependence—i.e., how long the start- and the end-of-the-period effect persists. Lastly, the paper provides formal statements for separately identifying time dependence and time preference, both of which are unobserved. By disentangling the two confounding, yet unobserved, time constructs, the study sheds light on the collective understanding of agents’ time assessment.

Finally, this study relates to the literature on sales management. Here, we focus on the stream of research addressing agents’ time assessment for its relevance to this study.² The theoretical studies on

² For a more comprehensive review of the sales force management literature, see, e.g., Coughlan and Sen (1989), Albers and Mantrala (2008), Rouziès and Onyemah (2018), and Chung et al. (2020).

this topic, which focus primarily on sales force compensation, find conflicting results regarding an agent’s intertemporal motivation. Traditional studies on intertemporal decision making advocate a linear commission contract (Hölmstrom and Milgrom 1987; Lal and Srinivasan 1993). The main argument for such a contract is that a pure commission structure induces the agent to exert a constant level of effort that is unaffected by past performance. Other incentive structures, in contrast, induce the agent to find ways to game the system, such as manipulating the timing of sales transactions. These studies, however, do not account for the intertemporal differences in allocation of effort—i.e., time dependence. If an agent’s cost of effort varies over time, some form of non-linear compensation contract, such as a combined bonus-plus-commissions structure, may be effective (Schöttner 2017). For example, for agents who are difficult to motivate during the start of the period, the chance to earn a lump-sum bonus induces them to exert greater effort at the outset of the performance-evaluation period. Hence, through the bonus component, the firm can provide start-of-the-period motivation at a lower cost compared to a pure commission structure. In contrast, when agents are difficult to incentivize towards the end of the period, a pure commission structure becomes more effective.

The empirical literature on sales compensation also finds conflicting results. Because of time discounting and intertemporal dynamics, some suggest that a linear commission scheme is optimal (Misra and Nair 2011; Kishore et al. 2013). However, an organization’s use of multiple compensation components—e.g., commission, quota bonus, overachievement commission, intermediary bonus—can motivate different types of agents (Chung et al. 2014). Furthermore, changes in the compensation structure can induce other behavior motives. For example, frequent-quota cycles can prevent low performers from giving up when confronted with bad luck early in the quota-evaluation cycle but may evoke agents to focus on low-ticket products (Chung et al. 2021b).

This study’s contribution to the sales management literature is twofold. First, the study jointly addresses the implications of agents’ time preference and dependence on sales management practices. Existing empirical research on sales management considers only agents’ time preference, whereas this study considers agent’s combined assessment of two separate time constructs, thereby providing a deeper understanding of agents’ intertemporal motivation. Furthermore, this study examines employee-shift scheduling, in addition to sales compensation, as means of effectively managing an organization’s sales force.

3. Institutional Details and Descriptive Analyses

This section describes the institutional details of the firm, including its compensation structure, quota-evaluation, and shift scheduling. In addition, the section presents model-free evidence on time dependence and preference, which leads naturally to the formulation of a model that includes intertemporal dynamics in Section 4.

3.1. Institutional Details

The firm under study is a Swedish electronics retailer that, at the time of the study (2015), operated about 100 company-owned stores. Its products include consumer electronics such as computer peripherals, mobile devices and their accessories, smart home and security devices, speakers and headsets, and car electronics and GPS devices. Product prices range from \$1 to \$500 or more, with an average price of about \$20.

The typical roles of a salesperson include determining customers’ needs, locating suitable products in the adjacent warehouse and finalizing the sale. The firm frequently trains its salespeople about sales techniques and products’ technical specifications. Its loyal, primary customer base consists of tech-savvy consumers seeking the technical expertise of the salespeople. Therefore, personal selling plays a critical role in the firm’s go-to-market strategy, and, thus, properly motivating salespeople and managing their activities are of vital importance to the firm’s management.

The data consist of salespeople’s daily sales revenue and their shift scheduling—workdays in a month and labor (working) hours for each workday—over a four-month period from January through April 2015. The study focuses on salespeople who stayed³ with the firm for the entire analysis period and those individuals with ten or more daily observations. After data clean-up, the final data comprise of 21,481 observations across 384 salespeople. **Table 1** shows the descriptive statistics of monthly sales, labor hours, and sales per hour (SPH).

The firm’s compensation structure consists of a fixed salary and a variable multi-tier-quota system. The rate of the variable commission is determined by a salesperson’s average SPH in a given month. **Table 2** provides the specifics of the quota-commission structure, and **Figure 1** shows a graphical illustration. A salesperson’s average SPH at the end of the quota-evaluation cycle (i.e., a month) determines the commission rate, categorized in five tiers, with the salesperson receiving a commission for every dollar of sales at the respective rate. For example, if a salesperson’s monthly sales total \$24,500 by

³ The firm has low employee attrition. Only 1.42% of salespeople left the firm during the analysis period.

working 100 hours in that month, the person’s average SPH of \$245 would fall into tier 4 (and just short of tier 5). Hence, the salesperson would make 1.5% of \$24,500 in sales, which equals \$368 in commission pay for that month.

A few additional points about the compensation structure are noteworthy. First, the commission structure based on average SPH naturally controls for the variation in labor hours and, in turn, provides a fair and equitable measure across salespeople. Second, even if a salesperson reaches the highest commission tier during a month, his or her motivation remains intact because the high commission rate is applied to the realized sales amount at the end of the month; thus, in a sense, there is no cap on commission. Third, as a salesperson achieves each tier, he or she receives a step jump in pay from the discretely accelerating commission rates (as illustrated in **Figure 1**). Lastly, the cumulative nature of the payout structure raises potential concerns that salespeople who fall short early in a month lose motivation and give up because their chance of attaining quota by the end of the month is low.

Before the start of each month, the firm plans salespeople’s monthly shift schedules, consisting of workdays in a month and labor hours for each workday. Once salespeople’s shift schedules are set, the firm rarely alters them during the month, except under extraordinary circumstances. Hence, the salespeople take their assigned schedules as given and plan their effort accordingly.

3.2. Model-Free Evidence

Figure 2 shows the average performance in SPH by calendar days across the entire sales force. Notice the clear increase in performance around the start and the end of the month. There are two likely explanations: (1) during the earlier and later periods, sales agents become more psychologically motivated and, thus, incur lower disutility of effort—i.e., their utility is time-dependent; or (2) specifically towards the end of the month, compensation is less discounted due to temporal proximity, and, thus, agents exert more effort—i.e., their time preferences influence behavior.

The following subsections provide more-detailed evidence of time dependence and preference.

3.2.1. Time Dependence

Table 3 reports the results of a regression analysis with SPH as the dependent variable and time-dependence variables as the explanatory variable. The two time-dependence variables—start of the period and end of the period—are set as the first and last five workdays, respectively, of each sales agent. Note that, due to differences in agents’ shift schedules, there is variation in their starting and ending

days. The results in the first column show positive and highly significant effects for both time dependent behaviors, consistent with the illustration in **Figure 2**.

Another possible reason for the increase in performance during the start and the end of the month is demand seasonality— i.e., consumers are more likely to shop in these periods. The variation in starting and ending days, to a certain degree, mitigates such a concern. Nevertheless, we test for statistical evidence of seasonality in the data. The second column in **Table 3** reports the results of a restricted analysis, which excludes observations from the first and last five “calendar” days. Hence, the analysis captures the start- and the end-of-period effects that arise only during mid-month— i.e., from the agents whose workdays start late or end early during the month. Consistent with the above results, the time-dependence variables remain significant, and, thus, we find no direct statistical evidence of demand seasonality.

3.2.2. Time Preference

The relation between sales agents’ cumulative performance—distance-to-quota (DTQ)—and temporal proximity to compensation provides evidence of time preference—forward-looking behavior (Chung et al., 2014, 2021a). Proximity to compensation affects only the performance of agents with a reasonable chance of making the quota and not that of agents who are unlikely to meet the quota and, thus, give up. Hence, we divide agents by their cumulative SPH achieved: if $SPH > \$90$, there is some probability of making the lowest-tier quota of \$140; if $SPH < \$90$, meeting the quota is unlikely. Furthermore, as the month nears its end and performance accumulates, the opportunity for a rebound diminishes. **Table 4** reports the results of regression analyses with daily sales as the dependent variable and the cumulative SPH (DTQ) as the explanatory variable, separately for the two groups of agents and for each of the four quartiles of a month. As forward-looking behavior suggests, the cumulative SPH is significant throughout the month for agents who have exceeded \$90. However, for agents below \$90, the variable becomes insignificant towards the end of the month, when they give up on the incentive.

4. Model

This section presents a dynamic model of an agent’s decision making that takes into account time dependence and preference. The discussion proceeds in three parts: (i) sales response and utility functions; (ii) compensation and state variables; and (iii) agent’s time dependence and preference.

An agent derives utility from compensation and disutility from effort. Compensation is nonlinear and cyclical, and it depends on the history of performance within a compensation cycle (month). At the

beginning of each compensation cycle, the agent knows of his or her predetermined shift schedule—workdays and labor hours per each work day.

4.1. Sales Response and Utility Functions

Agent i in month m at time t (day) generates sales revenue r_{imt} such that

$$r_{imt} = h_{imt} \cdot q_{imt}, \quad (1)$$

where h_{imt} is the labor hour and q_{imt} is sales per hour (SPH).⁴ The SPH is a function of the agent's baseline ability α_i , his or her effort e_{imt} ,⁵ and an idiosyncratic shock ξ_{imt} such that

$$q_{imt} = \exp(\alpha_i + e_{imt} + \xi_{imt}) \quad (2)$$

or in a logarithmic form, $\ln(q_{imt}) = \alpha_i + e_{imt} + \xi_{imt}$. The idiosyncratic shock ξ_{imt} follows a normal distribution with mean zero and variance σ_ξ^2 . The agent knows the distribution of the shock but does not observe its realization when making his or her effort decision.

The sales response functions in **Equations (1) and (2)** associate unobserved effort e_{imt} with observed revenue r_{imt} . The agent's daily performance r_{imt} accumulates over time through the evolution of state variables $s_{i,t+1} = f(r_{imt}, s_{imt}; \psi_{im})$, where $f(\cdot)$ denotes the state transition function. At the end of the quota-evaluation cycle,⁶ the accumulated performance, together with total labor hours, determines the agent's average SPH and, in turn, the amount of compensation W_{imt} (Section 4.2 presents details of the state variables and the compensation scheme).

At each time t , the agent derives instantaneous utility based on compensation and effort such that

$$\tilde{U}_{imt} = M(W_{imt}) - C(e_{imt}).$$

The positive monetary utility $M(W_{imt})$ is a function of compensation W_{imt} . The agent concurrently incurs disutility $C(e_{imt})$ as a function of effort e_{imt} , which, in turn, affects the sales performance in the contemporaneous period. Note that the agent exerts effort each day, whereas he or she earns compensation only at the end of the quota-evaluation cycle.

The above utility function is *ex-post* in the sense that the performance shock ξ_{imt} , which affects W_{imt} through q_{imt} , is as yet unrealized by the agent when making his or her effort choice. Hence, the agent

⁴ The notation m is necessary because an agent's shift schedule (workdays and labor hours for each workday) varies across months.

⁵ In the study's empirical application, effort is normalized by labor hours. However, the model easily extends to accommodate total effort.

⁶ The quota-evaluation cycle in the empirical setting is a month. Note again that the unit of observation is a day.

takes expectation of compensation W_{imt} , conditional on effort e_{imt} and current states s_{imt} , when making his or her effort decision. In this regard, the *ex-ante* utility function becomes

$$U_{imt} = E[M(W_{imt}) | e_{imt}, s_{imt}] - C(e_{imt}),$$

where functions M and C take the following parametric structure:

The monetary utility function M takes a mean-variance utility form such that

$$E[M(W_{imt}) | e_{imt}, s_{imt}] = E[W_{imt} | e_{imt}, s_{imt}] - \gamma_i \text{Var}[W_{imt} | e_{imt}, s_{imt}],$$

where γ_i represents the agent's risk preference.⁷ The vector of state variables s_{imt} contains information related to compensation, including the shift schedule—remaining number of workdays in the month and labor hours for each of those days—and the performance history—cumulative revenue and cumulative labor hours—until day t .

The disutility function C is quadratic in effort, augmented by labor hours, such that

$$C(e_{imt}) = c(z_{imt}; \Theta) \cdot h_{imt} \cdot e_{imt}^2, \quad (3)$$

where $c(z_{imt}; \Theta)$ denotes the level of disutility. It represents the agent's ease and flexibility in exerting effort across time. We model an agent's time dependence by allowing a vector of *time states* z_{imt} to affect the level of disutility $c(z_{imt}; \Theta)$, where vector Θ includes the corresponding parameters of time dependence. In this manner, these time states affect the agent's level of effort (Section 4.3 presents details of time dependence). The functional form in **Equation (3)** implies that disutility is strictly increasing and convex in effort e_{imt} ; and increasing in labor hours h_{imt} . The unit of effort is normalized per hour, per the sales response function in **Equation (2)**.

Given the above specifications, the agent's instantaneous utility at time t becomes

$$U_{imt} = E[W_{imt} | e_{imt}, s_{imt}] - \gamma_i \text{Var}[W_{imt} | e_{imt}, s_{imt}] - c(z_{imt}; \Theta) \cdot h_{imt} \cdot e_{imt}^2. \quad (4)$$

4.2. Compensation and State Variables

The commission tier Q_{imt} —determined by an agent's average SPH—represents the firm's compensation structure.⁸ Formally, Q_{imt} is as follows:

⁷ The mean-variance utility implies constant absolute risk aversion (CARA).

⁸ Although illustrated based on the institutional setting, this study's model is applicable to a wide class of nonlinear and cyclical compensation systems.

$$Q_{imt} = \begin{cases} 0.0027 & \text{if } 140 \leq s_{1,im,t+1} / s_{2,im,t+1} < 180 \text{ and } s_{2,im,t+1} = H_{im}, \\ 0.0067 & \text{if } 180 \leq s_{1,im,t+1} / s_{2,im,t+1} < 200 \text{ and } s_{2,im,t+1} = H_{im}, \\ 0.0090 & \text{if } 200 \leq s_{1,im,t+1} / s_{2,im,t+1} < 235 \text{ and } s_{2,im,t+1} = H_{im}, \\ 0.0150 & \text{if } 235 \leq s_{1,im,t+1} / s_{2,im,t+1} < 250 \text{ and } s_{2,im,t+1} = H_{im}, \\ 0.0200 & \text{if } 250 \leq s_{1,im,t+1} / s_{2,im,t+1} \text{ and } s_{2,im,t+1} = H_{im}, \\ 0 & \text{otherwise.} \end{cases}$$

The state variables $s_{1,imt}$ and $s_{2,imt}$ denote an agent's cumulative sales and his or her cumulative labor hours, respectively, by the end of the previous shift; and H_{im} denotes the total hours assigned to the agent by the firm in month m .

Given the commission tier Q_{imt} , the agent receives compensation $W_{imt} = W(r_{imt}, h_{imt}, s_{imt}; Q_{imt})$ based on performance r_{imt} , labor hours h_{imt} , and state s_{imt} . The end-of-month commission is distributed in the following form:

$$W_{imt} = (s_{1,imt} + r_{imt}) \cdot Q_{imt}.$$

Note, again, that the Q_{imt} allocates compensation only on the last day of each month—i.e., $s_{2,im,t+1} = H_{im}$. During the other days of the month, $W_{imt} = 0$, and, thus, an agent's instantaneous utility depends solely on his or her disutility.

The state variables directly linked to compensation include: (i) the cumulative sales within the month $s_{1,imt}$; and (ii) the cumulative labor hours within the month $s_{2,imt}$. The state variables evolve as follows:

1. Cumulative sales

$$s_{1,itm} = \begin{cases} 0 & \text{if } t = 1, \\ s_{1,im,t-1} + r_{imt} & \text{otherwise.} \end{cases}$$

2. Cumulative labor hours

$$s_{2,imt} = \begin{cases} 0 & \text{if } t = 1, \\ s_{2,im,t-1} + h_{imt} & \text{otherwise.} \end{cases}$$

The cumulative sales evolve stochastically, based on the agent's effort. The cumulative labor hours evolve deterministically, based on the agent's monthly shift schedule $\mathbf{H}_{im} = \{h_{1,im}, h_{2,im}, \dots, h_{T,im}\}$, predetermined by the firm for $t = 1, 2, \dots, T$, where T is the total number of work days in each month.⁹ The vector $s_{imt} = \{s_{1,imt}, s_{2,imt}, z_{imt}, T, \mathbf{H}_{im}\}$ represents the state variables that directly affect compensation.

⁹ The number of work days differs across agents and over months. For notational brevity, we omit the dependence of T on i and m .

4.3. Time Dependence and Preference

The utility function in **Equation (4)**, when linked with the aforementioned course of actions, performance outcomes, and state transitions, naturally leads to a dynamic formulation of the model. The discussion proceeds with the two aspects of agents' time assessment: time dependence and time preference.

4.3.1. Time Dependence

To examine whether agents are more/less likely to exert effort at the start and/or end of a period, we associate their time dependence in the disutility function in **Equation (3)** by including the respective times in state z_{imt} . Let the level of disutility take the form of

$$c(z_{imt}; \Theta) = \theta_0 + \theta_1 z_{1,imt} + \theta_2 z_{2,imt},$$

where the time states $z_{1,imt}$ and $z_{2,imt}$ denote the start-of-the-period and the end-of-the-period, respectively. More formally,

$$\begin{cases} z_{1,imt} = 1 & \text{if } t \leq D_S \text{ and } 0 \text{ otherwise,} \\ z_{2,imt} = 1 & \text{if } T - D_E \leq t \text{ and } 0 \text{ otherwise,} \end{cases}$$

where D_S and D_E denote the duration of time dependence—in terms of workdays—which we are also able to identify from the data (see Section 5.2.1 for details). Hence, the parameter θ_0 represents an agent's time-independent disutility; and his or her disutility shifts by θ_1 and θ_2 if the workday falls within the first D_S days and last D_E days, respectively, of the shift schedule. The vector $\Theta = \{\theta_0, \theta_1, \theta_2\}$ consists of these parameters.

4.3.2. Time Preference

An agent's effort today yields a higher chance of achieving greater compensation at the end of the month. Hence, the agent's time preference plays an important role in determining his or her optimal effort. On the one hand, if an agent is perfectly forward-looking, he or she will effectively distribute effort throughout the month, thereby exerting close to a constant level of effort, which minimizes the overall disutility over time. On the other hand, if an agent is myopic and heavily discounts the future, he or she will have less incentive to exert effort in the earlier days of a month.

To capture the agents' time preferences, this study posits a quasi-hyperbolic discounting model. The model postulates that the utility from the j -th day in the future is discounted by $\beta\delta^j$ for $j = 1, 2, \dots, T-1$, where $\beta \in (0,1]$ and $\delta \in (0,1)$. The standard discount factor δ features exponential discounting—

geometric decay—and captures time-consistent discounting behavior. The present-bias factor β uniformly discounts all future utility; thus, it captures the short-term impatience and time-inconsistent-discounting behavior of the agent. Also note that the conventional exponential discounting model is a special case of the quasi-hyperbolic discounting model when $\beta = 1$.

The agent maximizes the expected sum of current and discounted future utilities over discrete time periods ($t = 1, 2, \dots, T$). Thus, the choice-specific value function $V(\cdot)$, defined as the discounted present value of the expected utility stream conditional on the choice of effort e_{imt} and state s_{imt} , becomes

$$V_{imt} = U_{imt} + \beta \mathbb{E} \left[\sum_{\tau=t+1}^T \delta^{\tau-t} \max_{e_{im\tau}} U_{im\tau} \mid e_{imt}, s_{imt} \right].$$

In the conventional exponential discounting model (where $\beta = 1$), one can formulate the above dynamic problem as a recursive system of U and V . However, the quasi-hyperbolic discounting model requires an additional nuisance value function to make the problem a recursive system:

$$V_{imt} = U_{imt} + \beta \delta \mathbb{E} \left[\max_{e_{im,t+1}} \tilde{V}_{im,t+1} \mid e_{imt}, s_{imt} \right], \quad (5)$$

where

$$\tilde{V}_{imt} = U_{imt} + \delta \mathbb{E} \left[\max_{e_{im,t+1}} \tilde{V}_{im,t+1} \mid e_{imt}, s_{imt} \right]. \quad (6)$$

Hence, the flow of future utility involves an additional value function \tilde{V}_{imt} caused by the agent's time inconsistency. That is, the agent is present-biased, and, thus, the optimal choice of effort in the present becomes different from that in the future. The vector $\Delta = \{\beta, \delta\}$ consists of the time-preference parameters.

5. Identification

This section presents identification arguments of the model parameters from the observed data. The data consist of a series of $(r_{imt}, h_{imt}, s_{imt})$ for $i = 1, 2, \dots, N$, $m = 1, 2, 3, 4$ and $t = 1, 2, \dots, T$, with the standard assumption that observations are independently and identically distributed across agents.

The discussion proceeds as follows: first, identification of the sales response function; second, identification of disutility, risk aversion, time preference and time dependence via solving the agent's objective function using backward induction; third, intuitive discussion of identification. The identification setup follows the empirical setting of this study. In the appendix, we provide identification arguments for a general infinite-horizon model that includes terminal actions.

5.1. Sales Response Function

The challenge in identifying the sales response function in **Equations (1) and (2)** is that the three components—the baseline ability α_i ; the optimal effort e_{imt}^* ; and the idiosyncratic sales shock ξ_{imt} —are all unobserved. The agent’s behavior in response to a nonlinear compensation structure provides conditions for separately identifying the baseline ability and the optimal effort. The key is to use the observations in which the optimal effort is trivially a corner solution (Chung et al. 2021a).

Assumption 1 (Corner Solution). *There exists a subset S with a positive probability measure in the support of s such that $\partial V(e, s) / \partial e \leq 0$ for any $e \geq 0$ and $s \in S$.*

The assumption states that the derivative of an agent’s value function with respect to effort is non-positive when his or her state lies in S , and, thus, the agent has no incentive to exert any effort. For example, S includes the case in which an agent is far from quota and, therefore, has given up on earning compensation for the quota-evaluation cycle. In such a case, because the optimal effort is trivially zero, the agent’s baseline ability is separately identified from his or her effort. The optimal effort as a function of the state variables is identified using a nonparametric regression method. Identification of the distribution of the remaining sales shock also follows.

Proposition 1. *Under Assumption 1, the agent’s baseline ability α_i , the optimal effort e_{imt}^* and the distribution of sales shock σ_ξ are identified.*

The proposition allows identification of the optimal effort as a function of state variables. Hereafter, we treat e_{imt}^* as if the value is observed. The distribution of the sales shock ξ_{imt} and the finite-horizon structure allows the backward induction of future payoffs.

5.2. Utility Function

Aside from the sales response function, the parameters of interest include those of time preference $\Delta = \{\beta, \delta\}$, disutility with time dependence $\Theta = \{\theta_0, \theta_1, \theta_2\}$, and risk aversion γ . Conditional on a known sales response function, one can identify these parameters by solving the agent’s maximization problem via backward induction—beginning from the last day of the compensation cycle and moving backward each period. Backward induction applies to any cyclical compensation structure, which depends on a history of performance over a finite horizon. For the remainder of this section, subscripts i and m are suppressed, whenever possible, for brevity.

5.2.1. Disutility, Risk Aversion, and Time Preference

For exposition purposes, we first illustrate identification of an agent's disutility, risk aversion and time preference, assuming that disutility is time-independent; thus, $z_{1t} = z_{2t} = 0$ for any t , and the level of disutility is constant across time at θ_0 . Subsequently, we relax this assumption and discuss identification of time dependence, θ_1 and θ_2 .

Consider an agent's optimization problem at T , the last period of the quota-evaluation cycle. Because there is no future payoff in the optimization problem, the agent's optimal effort is a solution to the *static* problem given by

$$\max_{e_T} V_T = \max_{e_T} U_T = \max_{e_T} \left\{ E[W \mid e_T, s_T] - \gamma \text{Var}[W \mid e_T, s_T] - \theta_0 \cdot h_T \cdot e_T^2 \right\},$$

which is equivalent to the utility function in **Equation (4)** for $t = T$. The first-order condition for the maximization problem is given by

$$\frac{\partial E(W \mid e_T^*, s_T)}{\partial e_T} - \gamma \cdot \frac{\partial \text{Var}(W \mid e_T^*, s_T)}{\partial e_T} - 2\theta_0 \cdot h_T \cdot e_T^* = 0. \quad (7)$$

The values $E(W \mid e_T, s_T)$ and $\text{Var}(W \mid e_T, s_T)$ are trivially obtained, given the distribution of the idiosyncratic shock σ_ξ . Conditional on the optimal effort e_T^* obtained from Proposition 1, the first-order condition in **Equation (7)** can be viewed as a regression of $\partial E(W \mid e_T^*, s_T) / \partial e_T$ on $\partial \text{Var}(W \mid e_T^*, s_T) / \partial e_T$ and $2h_T \cdot e_T^*$ with coefficients γ and θ_0 , respectively. Thus, the identification argument follows directly from that of a standard linear regression model.

Next, at $T-1$, the agent's maximization problem becomes

$$\max_{e_{T-1}} V_{T-1} = \max_{e_{T-1}} \left\{ -\theta_0 \cdot h_{T-1} \cdot e_{T-1}^2 + \beta \delta E[\max_{e_T} V_T \mid e_{T-1}, x_{T-1}] \right\}.$$

For $T-1$, the primitives of time preference, β and δ , are not separately identified, and only their product $\eta \equiv \beta\delta$ is. Further, note that time inconsistency, caused by disproportionate discounting between immediate and distant future payoffs, does not occur here because there is only one future payoff. The optimality condition for $T-1$ is given by

$$\eta \cdot \frac{\partial E[V(e_T^*, s_T) \mid e_{T-1}^*, s_{T-1}]}{\partial e_{T-1}} - 2\theta_0 \cdot h_{T-1} \cdot e_{T-1}^* = 0. \quad (8)$$

Because V_T is obtained in the previous step, one can trivially compute $E[V(e_T^*, s_T \mid e_{T-1}^*, s_{T-1})]$ and its derivative. The optimal effort e_{T-1}^* and disutility θ_0 are identified from Proposition 1 and **Equation (7)**,

respectively; thus, the product of discount factors η is the only unknown in **Equation (8)**, and, similar to the previous step, identification of η ($\equiv \beta\delta$) is straightforward.

By solving the agent's problem on day $T-2$, one can separately identify the two discount factors within η . At $T-2$, the agent's problem involves two future payoffs:

$$\max_{e_{T-2}} V_{T-2} = \max_{e_{T-2}} \left\{ -\theta_0 \cdot h_{T-2} \cdot e_{T-2}^2 + \beta \delta E[\max_{e_{T-1}} \tilde{V}_{T-1} \mid e_{im,T-2}, x_{im,T-2}] \right\}.$$

Different from the previous steps, the time-inconsistency problem arises from $T-2$. Note that the future value function in the above maximization equation is the nuisance, present-unbiased value function \tilde{V}_{T-1} in **Equation (6)** and *not* the present-biased value function V_{T-1} , as in **Equation (5)**.

Recall that the nuisance value function is defined as

$$\tilde{V}_{T-1} = \delta E \left[\max_{e_T} \tilde{V}_T \mid e_{T-1}, s_{T-1} \right] - \theta_0 \cdot h_{T-1} \cdot e_{T-1}^2,$$

which does not include the present-bias discount factor β . Let \tilde{e}_{T-1} denote the value that maximizes \tilde{V}_{T-1} . Thus, the optimality condition to maximize \tilde{V}_{T-1} is given by

$$\delta \cdot \frac{\partial E[\tilde{V}(e_T^*, s_T) \mid \tilde{e}_{T-1}, s_{T-1}]}{\partial e_{T-1}} - 2\theta_0 \cdot h_{T-1} \cdot \tilde{e}_{T-1} = 0, \quad (9)$$

which reflects the dependence of \tilde{e}_{T-1} on δ . Note that the condition in **Equation (9)** has a different discount factor from the optimality condition in **Equation (8)**. Hence, $\tilde{e}_{T-1} \neq e_{T-1}^*$, and, thus, the nuisance optimal effort \tilde{e}_{T-1} , as a function of s_{T-1} and δ , needs to be separately obtained using the identified values of θ_0 and V_T .

Reconstructing the value function V_{T-2} , using \tilde{e}_{T-1} and e_T^* , yields

$$\max_{e_{T-2}} V_{T-2} = \max_{e_{T-2}} \left\{ \eta \delta E[E[V(e_T^*, s_T) \mid \tilde{e}_{T-1}, s_{T-1}] \mid e_{T-2}, s_{T-2}] - \eta \theta_0 E[h_{T-1} \cdot \tilde{e}_{T-1}^2 \mid e_{T-2}, s_{T-2}] - \theta_0 \cdot h_{T-2} \cdot e_{T-2}^2 \right\}.$$

Thus, the optimality condition is given by

$$\eta \delta \cdot \frac{\partial E[E[V(e_T^*, s_T) \mid \tilde{e}_{T-1}, s_{T-1}] \mid e_{T-2}, s_{T-2}]}{\partial e_{T-2}} - \eta \theta_0 \cdot \frac{\partial E[h_{T-1} \cdot \tilde{e}_{T-1}^2 \mid e_{T-2}, s_{T-2}]}{\partial e_{T-2}} - 2h_{T-2} \cdot e_{T-2}^* = 0. \quad (10)$$

The only remaining unknown in the above equation is δ since η and θ_0 were identified in the previous steps. By solving this equation, one can identify δ and, thus, can recover β from $\beta = \eta/\delta$. Hence, we can separately identify the standard discount factor δ and the present-bias factor β .

The rank conditions below are sufficient to identify time preference.

Assumption 2 (Full Rank Conditions). *For the initial three steps in the backward induction, the following conditions are satisfied:*

- (1) $E(AA')$ has a full rank, where the random vector A is defined as $A = \begin{pmatrix} \partial \text{Var}(W \mid e_T^*, s_T) / \partial e_T \\ 2h_T \cdot e_T^* \end{pmatrix}$,
- (2) $E \left[\frac{\partial E[V(e_T^*, s_T \mid e_{T-1}^*, s_{T-1})]}{\partial e_{T-1}} \right] \neq 0$,
- (3) $E \left[\frac{\partial E[E[V(e_T^*, s_T \mid \tilde{e}_{T-1}, s_{T-1}) \mid e_{T-2}^*, s_{T-2}]]}{\partial e_{T-2}} \right] \neq 0$.

Proposition 2. *Under Assumptions 1 and 2, risk aversion γ , time-independent disutility θ_0 and time preference Δ —the present-bias factor β and the standard discount factor δ —are identified.*

Assumption 2-(1) implies that an agent’s effort affects the uncertainty in compensation and disutility in a linearly independent manner. This is necessary to identify risk aversion γ separately from disutility θ_0 in the first step of the backward induction. The assumption holds if $\text{Var}(W \mid e_T, s_T)$ is not a quadratic function of e_T , which is readily satisfied under various non-linear compensation structures in practice, including the piecewise linear scheme used in this study’s empirical application. Assumptions 2-(2) and 2-(3) serve as rank conditions for the second and third steps of the backward induction, respectively, which are required for identifying hyperbolic time preference. They require the choice of effort to have a lasting effect for at least two days. Otherwise, the agent’s choice of effort would simply be static and unaffected by the discount factors.

5.2.1. Time Dependence

To identify time dependence (θ_1, θ_2) , we present the identification results in two steps. First, we consider a general time dependence that is fully flexible, allowing the disutility parameters to depend on time t in an arbitrary fashion, and discuss the necessary restrictions for identification. Second, we apply the restriction to the study’s empirical setting and discuss identifying the duration of time-dependence.

To illustrate identification under general time dependence, let us restate an agent’s disutility as a series of parameters $\tau_t = \{\tau_1, \tau_2, \dots, \tau_T\}$ so that the disutility is fully time-dependent—i.e., each day has its own disutility parameter. In this case, identification of γ and τ_T using the maximization condition at time T still holds. However, consider the problem at day $T-1$ and its optimality condition in **Equation**

(8). The disutility function now depends on τ_{T-1} , which is different from τ_T and, thus, is not identified. Hence, the equation holds even if η and τ_{T-1} are multiplied by a constant. In other words, the scale of time preference η ($\equiv \beta\delta$) and time-dependent disutility τ_{T-1} is not identified—only their ratio is.¹⁰ Intuitively speaking, suppose that one observes an agent to exert a high value of effort at $T-1$. If disutility is set to be fully flexible over time, one cannot distinguish between a high discount factor (future compensation at T is not discounted much) and low disutility (effort is not too costly). In an extreme case, any data can be rationalized by a model in which $\beta = \delta = 1$; that is, there is no discounting, and τ_t rapidly changes over time.

Facilitating identification of time dependence requires restricting the variation in the agent's unknown disutility. Specifically, because there are two time-preference primitives β and δ , the reduction must occur for at least two dimensions in the parametric space.

Assumption 3 (Rank Condition under Dimension Reduction). *For general time dependence, the following conditions are satisfied:*

(1) *The disutility parameters $\mathbf{T} = \{\tau_1, \tau_2, \dots, \tau_T\}$ satisfy restrictions $R(\mathbf{T}) = \begin{pmatrix} r_1(\mathbf{T}) \\ r_2(\mathbf{T}) \end{pmatrix} = 0$ with*

$$\text{rank} \left(\frac{\partial R}{\partial \mathbf{T}} \right) \geq 2.$$

(2) $\frac{\partial}{\partial \delta} \left(\mathbb{E} \left[\frac{\partial \mathbb{E}[\tilde{V}(\tilde{e}_{t+1}, s_{t+1}) | e_t^*, s_t]}{\partial e_t} \right] \right) \neq 0$ for all $t=1, 2, \dots, T-1$.

Assumption 3-(1) imposes two restrictions on the time-dependence parameters, requiring that the restrictions be linearly independent with each other. Assumption 3-(2) implies that the standard discount factor δ has some effects on the first-order condition associated with the nuisance value function for any time t ; if this is violated, the effects of δ and β become identical and, thus, are not separately identified.

Proposition 3. *Suppose that Assumptions 1, 2-(1) and 3 hold. Then, τ_t for $t = 1, 2, \dots, T$ are identified subject to the dimension restriction. The time preference β , δ and risk aversion γ are separately identified.*

¹⁰ The ratio is identified as $\eta/\tau_{T-1} = 2h_{T-1} \cdot e_{T-1}^* \{\partial \mathbb{E}[V(e_T^*, s_T | e_{T-1}^*, s_{T-1})]/\partial e_{T-1}\}^{-1}$.

The proposition states that, for model identification, one needs to reduce the dimension of time dependence to $T-2$ or less.¹¹ In this study’s empirical setting, the dimension of disutility is set at three—start-of-the-period, middle-of-the-period, and end-of-the-period—and the disutility does not vary within each period group. More formally,

$$\begin{cases} \tau_S = \theta_0 + \theta_1 & \text{if } t \leq D_S, \\ \tau_M = \theta_0 & \text{if } D_S \leq t \leq T - D_E, \\ \tau_E = \theta_0 + \theta_2 & \text{if } T - D_E \leq t, \end{cases} \quad (11)$$

for the duration of time dependence D_S and D_E . Here, the first D_S workdays are the start-of-the- period, and the last D_E workdays are the end-of-the-period, with parameters θ_1 and θ_2 capturing time dependence of disutility in the respective periods.

The following proposition identifies the duration of time dependence.

Proposition 4. *Suppose that Assumptions 1, 2-(1) and 3-(2) hold. Then, the time-independent and time-dependent disutility $(\theta_0, \theta_1, \theta_2)$ and the duration of each period T_S and T_E are identified under the specification in Equation (11).*

5.3. Intuitive Discussion of Identification

In addition to the formal identification arguments described above, we discuss model identification in our empirical context. First, we provide intuition regarding the identification of static utility. Then, we discuss identification regarding time dependence and preference.

To identify unobserved effort and utility parameters, we turn to the relation between an agent’s performance and his or her state variables. The agent likely exerts more effort when he or she is close to quota than when far from quota. Thus, differences in sales performance at different DTQ identify effort and, thus, facilitate identification of the associated agent’s disutility (Misra and Nair 2011; Chung et al. 2014, 2021a). Suppose that there are two agents at the same DTQ, but one’s performance is higher than the other’s. This implies that the agent with better performance has lower disutility of effort. Similarly, suppose that there are two agents whose DTQ is far from quota— i.e., neither of them has any chance of meeting the quota, but one’s performance is higher than the other’s. This implies that the agent with better performance has higher baseline ability. The variation in sales, given effort and baseline ability, identifies the distribution of the idiosyncratic shock. The extent to which an agent over- or underperforms

¹¹ In practice, depending on the structure of the data, additional restrictions, such as the one used in this study’s empirical application, may be necessary to make the model tractable and parsimonious.

on quota identifies the risk-aversion parameter: a risk-averse agent would over- or underachieve in compensation-payout periods, whereas a risk-neutral agent would just meet quota.

For the time-preference parameters, an agent’s DTQ in non-bonus periods acts as an exclusion restriction to separately identify the standard discount factor and present-bias factor. Suppose that there are two agents who exert same amount of effort (and, thus, show similar performance) at the end of the month. However, suppose also that, in earlier days, one agent performs better than the other, even though both are at the same DTQ. This implies that the agent with high performance in these periods is more persistent, having a higher discount factor (lower discount rate). The hyperbolic discounting model is identified if there exist more than two periods with exclusion restrictions. The performance of an exponential discounter would be smoother over time than that of a hyperbolic discounter.

The time-dependence parameters are identified when there are any over- or underachievement, after accounting for time discounting, during the specified periods. For example, since time discounting posits that the value of the earlier period is always weakly lower than that of the future, any performance increase during the first several workdays, compared to the mid-month, identifies the start-of-the-period effect. The duration of time dependence is identified at the location in which the difference in excess/lesser performance is the most noticeable.

6. Estimation

The core of the estimation relies on solving the agent’s finite-horizon problem via backward induction from the last period $t = T$, using the two choice-specific value functions given by **Equations (5) and (6)**. The *present-biased* choice-specific value function in **Equation (5)** determines the optimal, yet present-biased, effort e_{it} and, thus, performance q_{it} , which enters the likelihood function for each period. The *present-unbiased* choice-specific value function in **Equation (6)** determines the optimal present-unbiased effort, which shapes the future value functions in the subsequent backward induction— i.e., the future values from previous periods. Note that, in each period, the optimal effort, either present-biased or present-unbiased, is the solution to the maximization problem across the choice-specific value functions, conditional on the agent’s states.

6.1. Individual Likelihood

From the inferred sales performance q_{it} , obtained through the estimation procedure, one can compute the likelihood of the agent’s observations. Given the data of an agent with observations over T periods, the agent’s likelihood is

$$L_i(\Omega_i; \mathbf{q}_i, \mathbf{x}_i) = \prod_{m=1}^M \prod_{t=1}^T \phi_{\xi,i}(\ln(\tilde{q}_{imt}) - \ln(q_{imt})),$$

where the vector $\Omega_i = \{\Delta_i, \Theta_i, \gamma_i, \alpha_i, \sigma_\xi\}$ is the set of parameters of time preference, time dependence, risk aversion, and the sales response function; \tilde{q}_{it} is the observed sales performance; and $\phi_{\xi,i}$ denotes the probability density function of a normal distribution with mean zero and variance σ_ξ^2 .

6.2. Unobserved Heterogeneity

Discrete segments accommodate unobserved heterogeneity (Kamakura and Russell 1989). Assume that sales agent i belongs to segment $k \in \{1, \dots, K\}$, with relative probabilities

$$j_k = \frac{\exp(\lambda_k)}{\sum_{k'} \exp(\lambda_{k'})}.$$

Let $L_{k,imt} = L(\Omega_k | k; q_{imt}, x_{imt})$ be the likelihood of parameters for agent i in month m at day t , conditional on unobserved segment k , given his or her data. Then, the likelihood of the segment-level parameters upon observing the agent's history is

$$L_k(\Omega_k; \mathbf{q}_i, \mathbf{x}_i) = j_k \left(\prod_{m=1}^M \prod_{t=1}^T L_{k,imt} \right).$$

By summing over all of the unobserved segments $k \in \{1, \dots, K\}$, the overall likelihood of agent i becomes

$$L(\Omega; \mathbf{q}_i, \mathbf{x}_i) = \sum_{k=1}^K L_k(\Omega_k; \mathbf{q}_i, \mathbf{x}_i),$$

where $\Omega = \{\Omega_1, \dots, \Omega_K\}$ contains the segment-level parameters. Hence, the log-likelihood over the N sample of individuals becomes

$$\sum_{i=1}^N \ln(L(\Omega; \mathbf{q}_i, \mathbf{x}_i)) = \sum_{i=1}^N \ln \left(\sum_{k=1}^K j_k \left(\prod_{m=1}^M \prod_{t=1}^T L_{k,imt} \right) \right).$$

7. Results

This section first presents the estimation results and discusses their implications. Then, it presents the results of counterfactual simulations that address the substantive question that this study poses: how should an organization design its shift schedule and compensation structure, taking into account agents' time dependence and preference? Finally, we compare simulated and actual sales from the post-data-

analysis period—accompanied by real changes in the firm’s quota-evaluation cycle—to validate the model’s prediction accuracy.

7.1. Parameter Estimates

The analysis reveals that the two-segment model, with the duration of time dependence $D=2$,¹² shows the best fit in terms of the Bayesian information criterion. **Table 5** reports the parameter estimates of the model. The time-independent disutility θ_0 , which represents the cost of effort, is 23.05 and 11.03 for segments 1 and 2, respectively. In a sense, the cost of effort is high for segment 1 (hereafter referred to as the *low* type) and low for segment 2 (hereafter referred to as the *high* type). The high types show time dependence with the start- and the end-of-the-period effects at -0.34 and -1.42 , respectively, shifting the cost of effort during those periods. Hence, these agents are more motivated—i.e., they incur lower disutility of effort during the start and the end of their quota-evaluation cycles. In contrast, the low types show limited time dependence with a smaller end-of-the-period effect and a statistically insignificant start-of-the-period effect.

For time preference, the standard discount factor δ is 0.72 and 0.99 and the present-bias factor β is 0.88 and 0.83 for the low and the high types, respectively.¹³ The low types profoundly discount their future payoffs, whereas the high types do not discount as much. Both segments show present-bias behavior.

Table 6 shows the share of the two segments and their descriptive characteristics. The low-type segment has a smaller share, at 38.96%, whereas the high-type segment represents a bigger share of 61.04%. Consistent with the parameter estimates, compared to the high types, the low types achieve lower sales and SPH despite similar working hours. The high types perform better, with higher SPH.

In summary, the following pattern appears in terms of agents’ behavior. Regarding time preference, the high-type agents’ motivation is intact throughout the month in attempt to maximize their less-discounted end-of-period compensation, whereas the low-type agents are myopic and continuously exert low effort. Regarding time dependence, the high type agents start off with extra effort at the outset of the month, but this strong motivation tends to wane after a couple of days. Towards the end of the period, both the low- and the high-type agents become extra motivated due to their time preference (i.e.,

¹² In the empirical application, we infer $D_S = D_E = D$ for simplicity.

¹³ Though the discount factor for the low type seems rather low, the range is consistent with studies that discuss psychological aspects such as pain and effort (Frederick et al. 2002).

temporal proximity to the goal) and time dependence (i.e., end-of-the-period effect). The combined effect of these two time constructs explains high performance at the end of the month, shown in the model-free analysis (Section 3.2).

7.2. Counterfactual Simulations

This section presents the results of counterfactual simulations that examine the effect of agents’ time assessment—dependence and preference—on their behavior, which can help organizations with their sales management practices. The counterfactuals evaluate agents’ sales performance and compensation according to changes in: (i) the quota-evaluation cycle; (ii) compensation schemes; and (iii) shift-scheduling.

The counterfactual simulations suppose that, given the segment sizes reported in **Table 6**, there are 39 low-type and 61 high-type sales agents, for a total of 100. For each regime, we simulate 200 paths per individual, using the parameter estimates of the model. The benchmark is the current sales management policy: the multi-tier-quota compensation structure at a monthly quota-evaluation cycle. Given the average monthly labor hours of 112, we set the shift schedule such that the agents work 7.5 hours a day for 15 days. **Table 7** reports the simulation results of the benchmark.

7.2.1. Alternative Quota-Evaluation Cycle

One of the primary tasks in setting a proper sales objective—the quota—is to determine its evaluation cycle. The theoretical predictions are that if the quota-evaluation cycle is long, the agents may put in extra effort to achieve a big reward, whereas if it is short, the agents benefit from constant motivation because they get a fresh start in each period (Chung et al. 2021b; Dai et al. 2014; 2015; Schöttner 2017). But how would heterogeneous agents respond to different quota cycles, taking into account their time assessment? To understand the mechanism, the first counterfactual examines a change in the quota-evaluation cycle from monthly to daily, while keeping other components constant.

Table 8 depicts the performance and compensation outcomes of the counterfactual simulation. The new regime leads to, on average, a 2.92% decrease in monthly sales. The change in performance is positive for the low-type segment but negative for the high-type segment. The daily-quota policy, by giving agents a fresh start each day while removing the role of time discounting and period-effects, benefits the low performers. The policy, however, turns the agents’ decision mostly static and, thus, eliminates the motivational role of a big reward, thereby discouraging the high performers.

Given the overall revenue decrease, are there any upsides to the daily quota-evaluation? The analysis reveals an interesting benefit: the variability (interpreted through the standard deviation) of performance across agents decreases significantly compared to that under the current policy (see **Table 8**). To understand why, note the negative feature of the benchmark monthly-quota cycle: if an agent is far from meeting quota, he or she likely gives up. Because each day is independent under the new policy, it mitigates agents' giving-up behavior and help them to exert consistent effort throughout the period. As a result, the variation across agents' performance decreases. The stability in sales can help organizations better forecast and manage their sales outcomes across agents and, thus, the sales performance of the outlets where they work.

Such a benefit, however, comes at an extra cost. To maintain a daily-quota cycle, the organization has to distribute 30% more in compensation. This is because the new policy is aimed at motivating the low-performing sales agents—the ones more difficult to motivate and, thus, whose marginal returns on compensation are smaller.

Overall, the counterfactual demonstrates the trade-off between long- and short-quota cycles. While reducing the quota cycle helps motivate the low-type performers and, in turn, decreases sales variation across agents, it also reduces the motivation for agents to stretch for the big award, thereby demotivating the high-type performers.

7.2.2. Alternative Compensation Schemes

The focal firm's existing variable compensation structure is a multi-tier-quota system. To understand the effect of each individual component of the compensation structure—commissions and bonuses by each tier—on agents' behavior, we use a second counterfactual to disentangle them and evaluate their effectiveness. More specifically, the counterfactual evaluates the outcomes of four plans: (i) a lump-sum bonus with the quota set at SPH \$140/Hr; (ii) a lump-sum bonus with the quota set at SPH \$180/Hr; (iii) a lump-sum bonus with the quota set at SPH \$200/Hr¹⁴; and (iv) a pure-commission structure.

The alternative plans are set to be cost-equivalent. That is, the bonus amount or the commission rate for each plan is determined such that the resulting total incentive amount matches the benchmark at \$93/person. The resulting bonus amounts are \$123.87, \$223.54, and \$295.49 for the bonus with quotas \$140/Hr, \$180/Hr, and \$200/Hr, respectively; the flat-rate commission is \$0.59/\$Sales. **Figure 3**

¹⁴ The \$235/Hr and \$250/Hr plans exhibit outcomes similar to that of the \$200/Hr plan and are omitted for brevity.

illustrates the alternative compensation structures, and **Table 9** shows the results of the counterfactual simulations.

Though one may intuitively expect lump-sum bonuses to better motivate the high types and commissions to help motivate the low types, we find a discrepancy across bonus plans in motivating different types of sales agents, depending on the *level* of the quota. The low-tier bonus (SPH \$140/Hr) helps motivate the low-type agents by reducing the bonus threshold. However, the low-tier bonus demotivates the high-type agents once they have secured the reduced bonus amount, which is within easy reach. Average performance is lower than the benchmark, but performance variation across agents also decreases. As the bonus moves up the tiers (SPH \$180/Hr and \$200/Hr), the high-type agents become motivated by the increased bonus amount; however, the higher quota levels induce low-type agents to give up.

The pure-commission plan decreases performance significantly. The demotivation of high-type agents is intuitive—the big-reward bonus is no longer in place, and the policy’s upside potential is smaller compared to the benchmark. Interestingly, however, the performance of the low-type agents also declines. To understand why, note that the pure-commission plan compensates for every unit of sales (see **Figure 3**), whereas the benchmark and other plans have a quota floored at \$140/Hr before any compensation is made. Because, now, the firm must pay for any performance, the amount of compensation to subpar performers increases. This implies that, to be cost-equivalent with the benchmark, the commission rate would go down and, thus, the pure-commission plan fails to motivate either group of agents.

Overall, from a pure return-on-investment perspective, a quota-bonus plan with an aspirational quota produces good performance outcomes. However, the benefits come at the cost of a large variation in sales across agents and over time.

7.2.3. Redesigning the Shift Schedule

The counterfactual in this section discusses a more direct application of understanding agents’ time dependence and preference. The results in Section 7.1 illustrate how the high types are forward-looking and have a positive start-of-the-period effect, whereas the low types are myopic and have limited time dependence during the outset of the period. This naturally implies that the former group of agents are better motivated in the earlier period and the latter in the later period.

Under the hypothetical scenario that the firm has knowledge of agents’ time dependence and preference, we redesign the shift schedule to better align it with each type’s characteristics. That is,

instead of allocating a flat 7.5 labor hours for all agents, we allocate more labor hours for the high types during the earlier days (and fewer during the later days) and more hours for the low types during the later days (and less during the earlier days). More specifically, the high types are assigned 10 hours for the first 7 days, 7.5 hours for the 8th day, and 5 hours for the remaining 7 days; and, conversely, the low types are assigned 5 hours for the first 7 days, 7.5 hours for the 8th day, and 10 hours for the remaining 7 days. To keep the daily total labor hours constant at the firm level, the reassignment is made only for 39 agents (the size of the low-type segment) in each segment, for a total of 78 agents.¹⁵ The remaining 22 agents in the high-type segment were assigned a flat 7.5 hours for 15 days.

Table 10 shows the effectiveness of the redesign. Overall performance increases by 1.88%, with both segments reporting increased performance. Compensation also increases to accompany the increase in performance. Although organizations typically have some information about their employees' characteristics, we would like to caution the reader regarding this counterfactual, as it relies on the assumption that the firm has precise knowledge of agents' time assessment. Nevertheless, this counterfactual demonstrates the value of understanding agents' time dependence and preference.

7.2.1. Effect of Time Assessment

To determine the effect of various elements of time assessment on the firm's sales outcome, the last counterfactual simulation examines alternative scenarios in which the agents are *not* influenced by time. For instance, the effect of agents' overall time assessment is captured by the change in sales without time preference ($\delta=\beta=1$) and time dependence ($\theta_1=\theta_2=0$). Hence, it provides a comparative static of the effect of agents' time assessment on the firm's sales outcome. **Table 11** shows the results.

As expected, the absence of agents' time preference has a positive effect on sales. More specifically, if agents do not discount their future payoffs, performance will increase by a significant 17.11%. In terms of time dependence, the start-of-period effect, seen among the high-type agents, has a slightly positive effect of 0.31% on sales. The stronger end-of-period effect encourages sales by 2.80%. With the two effects combined, agents' time dependence results in a positive effect of 3.06% on sales.

Overall, the comparative static shows how agents' time assessment has a considerable effect on the firm's performance. Hence, to maintain sales force motivation, an organization must first understand how agents assess time and then undertake proactive measures to mitigate the negative effects—e.g.,

¹⁵ The reassignment complies with Swedish regulations.

offering goal reminders or providing daily performance feedback—and promote the positive effects—e.g., making the start and the end of period more salient.

7.4. Field Validation

In May 2015, the focal firm changed its quota-evaluation cycle from monthly to daily. This section validates the accuracy of our model by comparing the actual data and the simulated outcomes based on the counterfactual analysis. Different from the previous section, the current analysis simulates based on the actual shift schedule—work days and labor hours—obtained from the new data.

Figure 4 compares the actual (dotted line) and projected (solid line) performance outcomes. The simulated data mimic the general trend, though are slightly less cyclical. Overall, the simulated performance fits the actual outcomes well, with a mean absolute percentage error of 1.90% on aggregate. Therefore, the comparison attests to the model’s accuracy in capturing agents’ causal behavior and its ability to predict and evaluate counterfactual outcomes under various alternative settings.

8. Conclusion

Understanding how agents assess their time is important for organizations for a number of reasons. First, it provides guidance on the design of an effective compensation structure. Various compensation systems, which are often dynamic in nature, appeal to different types of agents who are heterogeneous in their time assessment. Moreover, it also has implications for determining how often performance should be evaluated. Myopic agents are likely better motivated under the short-evaluation cycle, whereas forward-looking ones may put in extra effort to achieve a big reward under the long-evaluation cycle. Lastly, agents’ time assessment affects their performance in response to shift schedules. By understanding when and for how long agents’ motivations are intact, an organization can tailor the shift schedule to different types of agents according to their time assessment.

This study develops and estimates a dynamic structural model of agents’ time assessment. The model considers behavioral elements of time dependence and preference, which are unobserved yet latent in agents’ dynamic allocation of effort. By illustrating how sales agents assess their time, the study has implications for determining the duration of the quota-evaluation cycle, selecting the right compensation schemes, and designing shift schedules.

The following summarizes the results. First, a short quota-evaluation cycle benefits the myopic low performers by giving them more frequent fresh starts, whereas a long quota-evaluation cycle benefits the forward-looking high performers by offering a chance at a big reward. Furthermore, a short quota-

evaluation cycle reduces the variability of performance across agents: it mitigates the agents' giving-up behavior and helps them exert consistent effort throughout the period, thereby allowing an organization to better forecast and manage its sales outcomes.

Second, a quota-bonus plan with an appropriate quota improves overall outcomes, driven mainly by the improved performance by the high-type agents. However, the performance increase comes at a cost—the low-type agents are more likely to give up, resulting in greater variation in sales across agents and time.

Third, an organization can redesign its shift schedule to better align with agents' time assessment. By allocating more labor hours during the early period for the forward-looking agents who possess strong start-of-period motivation and more hours during the later period for the myopic agents who are less time-dependent, an organization can improve on its sales outcomes.

Methodologically, the study provides formal identification conditions for which time preference and dependence are separately identified. Specifically, it considers identification of time dependence and its duration in a fully flexible setting under which instantaneous utility depends arbitrarily on time. The restrictions for identifying the two unobserved elements of time assessment are discussed and sufficient conditions are provided.

In addition, the study provides a field validation, which compares post-analysis actual and counterfactual outcomes to verify the accuracy of the model. Such validation attests to the predictability and applicability of the model under alternative compensation and shift-schedule designs. Hence, this study offers a practical tool for organizations to understand how and when their agents are best motivated and, thus, to effectively align their sales management practices with their agents' time assessment.

In summary, this study offers a rigorous, yet practical, treatment of time assessment that is readily applicable in practice. We believe that understanding how agents' motivations vary over time will help organizations better align their sales agents' interests with their own and, therefore, benefit both parties alike.

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Table 1: Descriptive Statistics

| Variable | Mean | S.D. |
|------------------------|--------|-------|
| Monthly sales | 16,917 | 5,544 |
| Monthly labor hours | 112 | 25 |
| Sales per hour | 150 | 31 |
| Number of sales agents | 384 | |

Notes. Sales are in U.S. dollars, converted using an approximate exchange rate for confidentiality.

Table 2: Variable Compensation Structure

| Tier | 1 | 2 | 3 | 4 | 5 |
|---------------------|------|------|------|------|------|
| Sales per hour | 140 | 180 | 200 | 235 | 250 |
| Commission rate (%) | 0.27 | 0.67 | 0.90 | 1.50 | 2.00 |

Notes. Sales are in U.S. dollars, converted using an approximate exchange rate for confidentiality.

Table 3: Performance and Time Dependence

| Variable | Sales per hour | |
|------------------------|-------------------------|-------------------------|
| | Full | Restricted |
| Intercept | 148.22 (0.61) | 148.18 (0.60) |
| Start-of-the-period | 5.85 (0.96) | 2.55 (1.24) |
| End-of-the-period | 7.53 (0.96) | 2.09 (1.29) |
| Number of observations | 21,481 | 14,390 |

Notes. Dependent variable: sales per hour. The full analysis includes all observations; the restricted analysis excludes the first and last five calendar days. Standard errors are in parentheses. Significance at the 0.05 level appears in boldface.

Table 4: Performance and Time Preference

| State | Variable | Daily performance | | | |
|---------------------|---|-------------------|----------------|----------------|----------------|
| | | Q1 | Q2 | Q3 | Q4 |
| Sales per hour > 90 | Intercept | -612.59 | -724.81 | -652.55 | -784.39 |
| | | (29.06) | (32.14) | (31.64) | (35.52) |
| | Cumulative sales per hour (distance to quota) | 4.20 | 5.18 | 5.45 | 5.95 |
| | | (0.13) | (0.16) | (0.16) | (0.18) |
| Sales per hour < 90 | Labor hour | 143.65 | 139.24 | 123.65 | 142.73 |
| | | (2.99) | (3.20) | (3.08) | (3.41) |
| | Intercept | -278.52 | -384.34 | -464.90 | -441.29 |
| | | (146.96) | (151.36) | (148.18) | (235.59) |
| | Cumulative sales per hour (distance to quota) | 4.46 | 6.39 | 7.50 | 3.99 |
| | | (1.62) | (1.59) | (1.63) | (2.87) |
| | Labor hour | 88.77 | 67.71 | 72.83 | 117.91 |
| | | (11.58) | (12.58) | (10.99) | (17.95) |

Notes. Dependent variable: daily sales. Cumulative sales per hour (SPH) are those by the previous day. Each column shows results for quartile periods of a month. The top and bottom half of the table show results of sales agents whose states are SPH > 90 and SPH < 90, respectively. Standard errors are in parentheses. Significance at the 0.05 level appears in boldface.

Table 5: Parameter Estimates

| Parameter | Segment 1 | Segment 2 |
|---|--------------|--------------|
| <i>Time preference</i> | | |
| Standard discount factor, δ | 0.72 | 0.99 |
| | (0.29) | (0.01) |
| Present-bias factor, β | 0.88 | 0.83 |
| | (0.32) | (0.09) |
| <i>Utility function – Time dependence</i> | | |
| Disutility of effort, θ_0 | 23.05 | 11.03 |
| | (0.23) | (0.15) |
| Start-of-the-period, θ_1 | -7.01 | -0.34 |
| | (6.58) | (0.01) |
| End-of-the-period, θ_2 | -1.04 | -1.42 |
| | (0.18) | (0.09) |
| Risk aversion, γ | 0.00 | 0.00 |
| | (0.00) | (0.00) |
| <i>Sales response function</i> | | |
| Baseline performance, α | 4.82 | |
| | (0.00) | |
| SD of performance shock, σ_ξ | 0.45 | |
| | (0.05) | |
| Segment probability, λ | 0.64 | 1.000 |
| Log-likelihood | -13,216 | |
| Bayesian information criterion | 26,583 | |

Notes. Significance at the 0.05 level appears in boldface. SD denotes standard deviation.

Table 6: Segment Characteristics

| Variable | Segment 1 | Segment 2 |
|--|-----------|-----------|
| Monthly sales | 13,674 | 19,290 |
| Monthly labor hours | 109 | 114 |
| Average SPH (\$sales/hour) | 126 | 168 |
| Segment Size (%) | 38.96 | 61.04 |
| <i>Notes.</i> Sales and SPH are in U.S. dollars, converted using an approximate exchange rate for confidentiality. | | |

Table 7: Counterfactual Simulation: Benchmark

| Counterfactual simulation | | Total | Within segment | |
|---|------|--------|----------------|-----------|
| | | | Segment 1 | Segment 2 |
| <i>Current policy</i> | | | | |
| Monthly sales | Mean | 17,983 | 15,461 | 19,596 |
| | SD | 4,446 | 1,879 | 4,829 |
| Monthly variable compensation | Mean | 93 | 21 | 139 |
| | SD | 152 | 26 | 179 |
| <i>Notes.</i> Monthly sales and compensation amount are in U.S. dollars, converted using an approximate exchange rate for confidentiality. SD denotes standard deviation. | | | | |

Table 8: Counterfactual Simulation: Quota-Evaluation Cycle

| Counterfactual simulation | | Total | Within segment | |
|-------------------------------|----------|--------|----------------|-----------|
| | | | Segment 1 | Segment 2 |
| <i>Daily-quota cycle</i> | | | | |
| Monthly sales | Mean | 17,457 | 16,298 | 18,199 |
| | (Change) | −2.92% | 5.41% | −7.13% |
| | SD | 2,293 | 1,931 | 2,172 |
| Monthly variable compensation | Mean | 121 | 97 | 137 |
| | (Change) | 30.54% | 356.88% | −1.23% |
| | SD | 59 | 49 | 59 |

Notes. Monthly sales and compensation amount are in U.S. dollars, converted using an approximate exchange rate for confidentiality. The change denotes percentage changes compared to the benchmark. SD denotes standard deviation.

Table 9: Counterfactual Simulation: Compensation Structure

| Counterfactual simulation | | Total | Within segment | |
|---|----------|---------|----------------|-----------|
| | | | Segment 1 | Segment 2 |
| 1-1. Bonus: \$123.87 if SPH is above \$140/Hr | | | | |
| Monthly sales | Mean | 16,538 | 15,633 | 17,116 |
| | (Change) | −8.04% | 1.12% | −12.65% |
| | SD | 1,740 | 1,852 | 1,354 |
| 1-2. Bonus: \$223.54 if SPH is above \$180/Hr | | | | |
| Monthly sales | Mean | 18,079 | 15,399 | 19,793 |
| | (Change) | 0.54% | −0.40% | 1.01% |
| | SD | 3,348 | 1,923 | 2,885 |
| 1-3. Bonus: \$295.49 if SPH is above \$200/Hr | | | | |
| Monthly sales | Mean | 18,425 | 15,361 | 20,385 |
| | (Change) | 2.46% | −0.65% | 4.03% |
| | SD | 4,168 | 1,855 | 4,029 |
| 2. Commission: \$0.59/Sale | | | | |
| Monthly sales | Mean | 15,676 | 15,400 | 15,853 |
| | (Change) | −12.83% | −0.39% | −19.01% |
| | SD | 1,894 | 1,825 | 1,892 |

Notes. Monthly sales and compensation amount are in U.S. dollars, converted using an approximate exchange rate for confidentiality. The change denotes percentage changes compared to the benchmark. Bonus plans for SPH above \$235/Hr and \$250/Hr show similar patterns and are omitted for brevity. SD denotes standard deviation.

Table 10: Counterfactual Simulation: Shift Schedule

| Counterfactual Simulation | | Total | Within Segment | |
|-------------------------------|----------|--------|----------------|-----------|
| | | | Segment 1 | Segment 2 |
| <i>Daily Quota-Evaluation</i> | | | | |
| Monthly Sales | Mean | 18,322 | 15,479 | 20,139 |
| | (Change) | 1.88% | 0.12% | 2.77% |
| | SD | 4,805 | 1,971 | 5,168 |
| Monthly variable compensation | Mean | 109 | 21 | 166 |
| | (Change) | 17.56% | 0.37% | 19.23% |
| | SD | 172 | 28 | 200 |

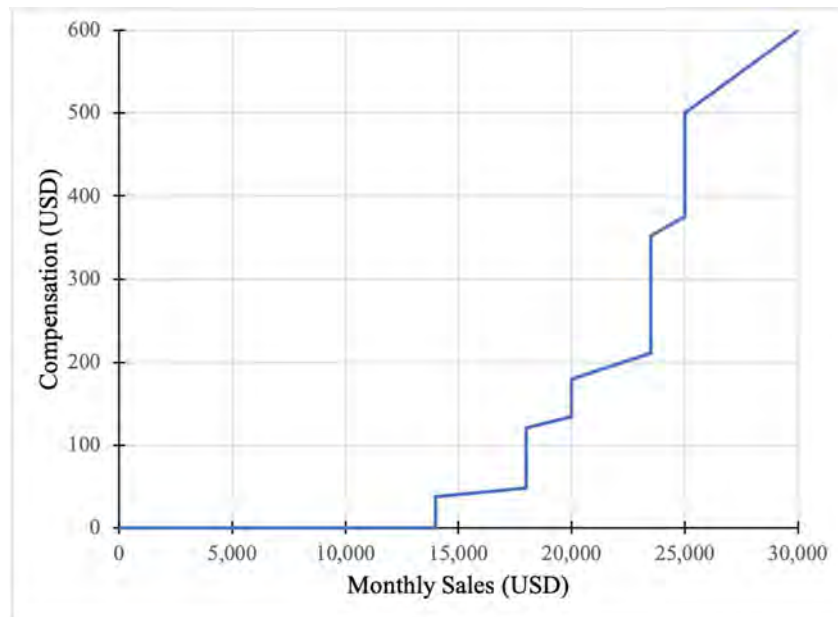
Notes. Monthly sales and compensation amount are in U.S. dollars, converted using an approximate exchange rate for confidentiality. The change denotes percentage changes compared to the benchmark. SD denotes standard deviation.

Table 11: Impact of Time Assessment

| Change in sales (%) under absence of | Total | Within segment | |
|--|-------|----------------|-----------|
| | | Segment 1 | Segment 2 |
| Time assessment ($\delta=\beta=1$; $\theta_1=\theta_2=0$) | 10.18 | 3.32 | 13.63 |
| Time preference ($\delta=\beta=1$) | 17.11 | 3.69 | 23.88 |
| Time discounting ($\delta=1$) | 1.93 | 3.08 | 1.35 |
| Present bias ($\beta=1$) | 14.21 | 0.08 | 21.34 |
| Time dependence ($\theta_1=\theta_2=0$) | -3.06 | -0.02 | -4.60 |
| Start-of-period effect ($\theta_1=0$) | -0.31 | 0.00 | -0.47 |
| End-of-period effect ($\theta_2=0$) | -2.80 | -0.02 | -4.20 |

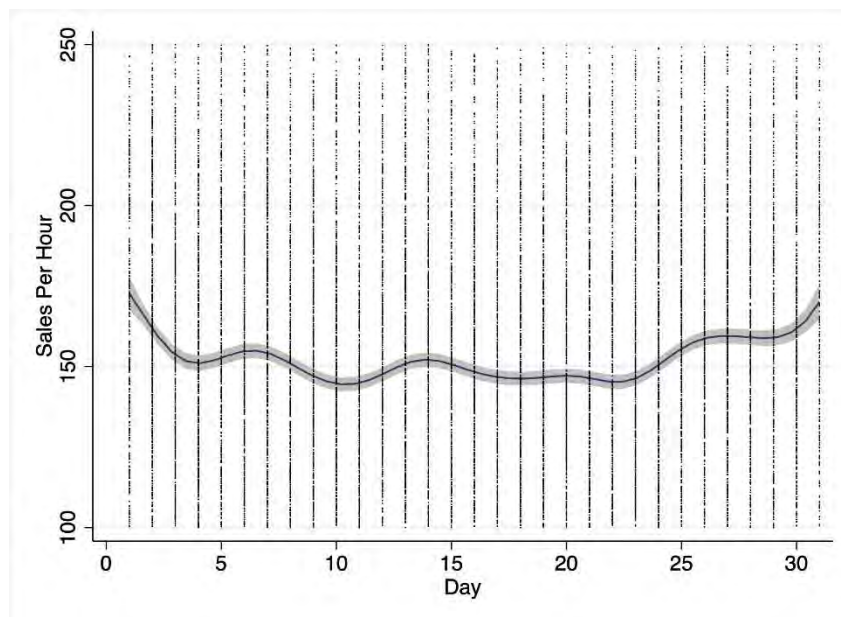
Notes. The change denotes percentage changes compared to the benchmark considering agents' time assessment—when both time preference and time dependence are present.

Figure 1: Relation Between Sales and Compensation



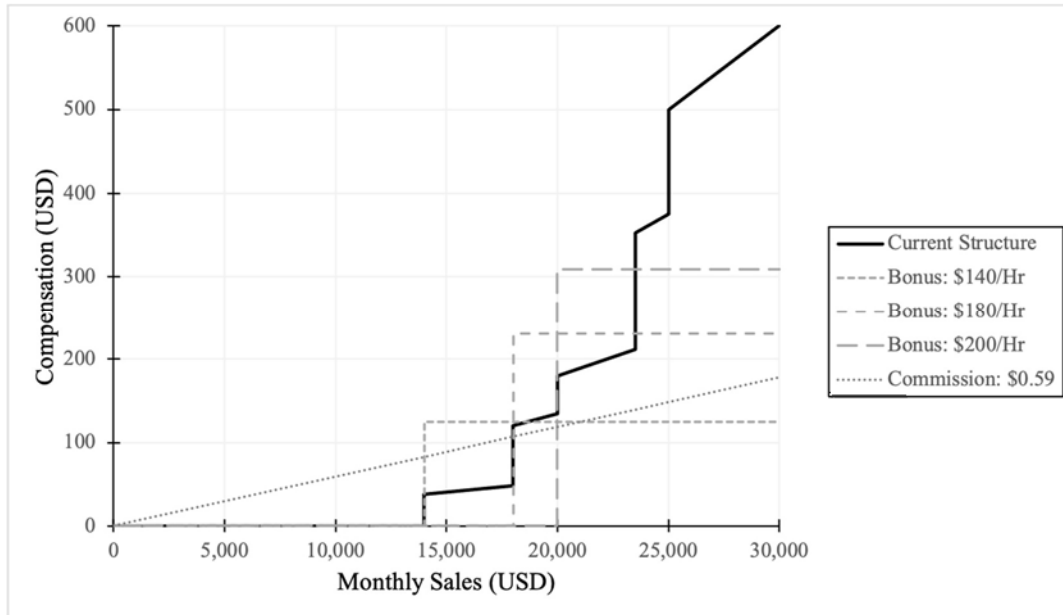
Notes. The figure illustrates monthly compensation, conditional on sales, for a salesperson assigned 100 hours a month.

Figure 2: Performance over Time



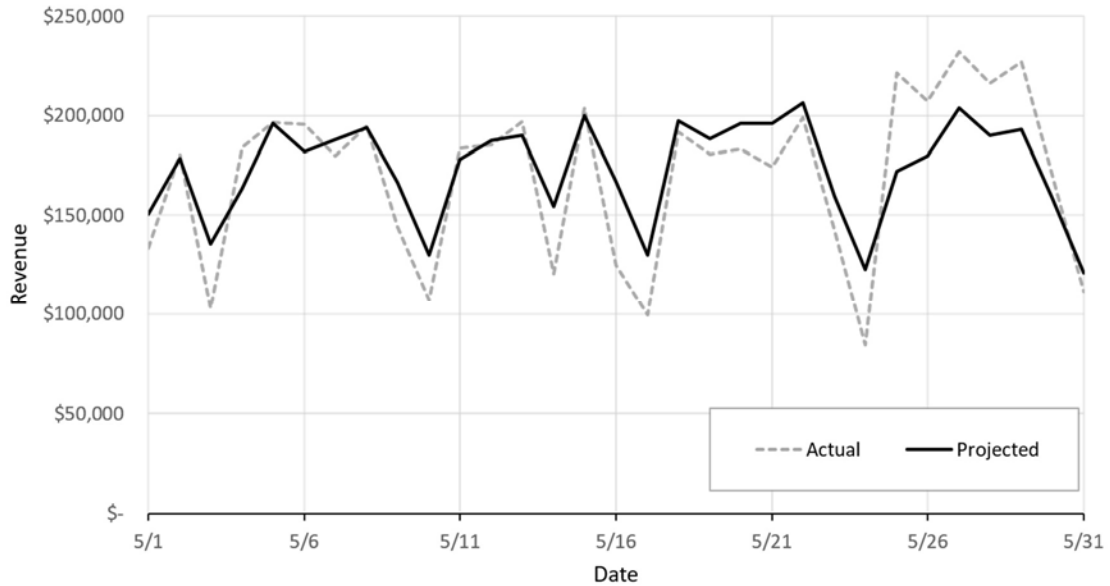
Notes. The y-axis depicts performance (sales per hour), and the x-axis shows the day in a month.

Figure 3: Counterfactual Simulation: Alternative Compensation Structures



Notes. The figure illustrates the payoffs from cost-equivalent compensation structures, conditional on sales, for a salesperson assigned 100 hours a month.

Figure 4: Field Validation



Notes. On May 1, 2015, the firm changed its quota-cycle from monthly to daily while keeping all other compensation components constant. The dotted line represents the actual outcome; the solid line represents the projected outcome (simulations) using the model parameters. The y-axis depicts the daily sales revenue across all sales agents, and the x-axis depicts dates during the post-analysis period.

Appendix

A. Proofs

Proof of Proposition 1. The agent, with knowledge of individual heterogeneity (α_i), chooses effort after observing state variables (s_{it}), and, thus, his or her optimal effort policy e_{it} is a function of s_{it} and α_i —i.e., $e_{it}=e(s_{it}, \alpha_i)$. Hence, the sales response function can be represented as

$$\ln(q_{it}) = \alpha_i + e(s_{it}, \alpha_i) + \xi_{it},$$

where q_{it} and s_{it} are observed; α_i and ξ_{it} are not.

By Assumption 1, if $s_{it} \in S$, the value function is a decreasing function of effort. Hence, the optimal effort is zero (i.e., $e(s_{it}, \alpha_i) = 0$ for $s_{it} \in S$), and, thus, sales become: $\ln(q_{it}) = \alpha_i + \xi_{it}$. Independence between ξ_{it} and s_{it} implies

$$\mathbb{E}[\ln(q_{it}) \mid s_{it} \in S] = \alpha_i + \mathbb{E}[\xi_{it} \mid s_{it} \in S] = \alpha_i,$$

from which α_i is identified.¹⁶

Once α_i is identified (from observations $s_{it} \in S$), the sales response (when $s_{it} \notin S$) takes the form of a nonparametric regression with a known intercept. That is, $e(s_{it}, \alpha_i)$ is now a regression function of $\ln(q_{it}) - \alpha_i$ on observed s_{it} and a known α_i . The optimal effort e_{it} is identified from $\mathbb{E}(\ln(q_{it}) - \alpha_i \mid s_{it}, \alpha_i)$. The distribution of the residuals is a consistent estimator for the distribution of ξ_{it} .

(Q.E.D.)

Proof of Proposition 2. Reordering Equation (7) leads to

$$\frac{\partial \mathbb{E}[W \mid e_T^*, s_T]}{\partial e_T} = \gamma \cdot \frac{\partial \text{Var}[W \mid e_T^*, s_T]}{\partial e_T} + 2\theta \cdot h_T \cdot e_T^*.$$

Multiplying the above by A , as defined in Assumption 2, and taking expectations on both sides yields

$$\mathbb{E} \left[A \cdot \frac{\partial \mathbb{E}[W \mid e_T^*, s_T]}{\partial e_T} \right] = \mathbb{E}[AA'] \begin{pmatrix} \gamma \\ \theta \end{pmatrix}.$$

Because $\mathbb{E}[AA']$ is invertible by Assumption 2, the following holds:

¹⁶ The individual-specific fixed effect α_i is consistently estimated in the case of a large T (i.e., $T \rightarrow \infty$). The empirical analysis estimates the fixed-effects parameters per segment, using daily observations for four months.

$$\begin{aligned}
\begin{pmatrix} \gamma \\ \theta \end{pmatrix} &= E[AA']^{-1} E \left[A \cdot \frac{\partial E[W \mid e_T^*, s_T]}{\partial e_T} \right] \\
&= E \left[\begin{pmatrix} \left(\frac{\partial \text{Var}[W \mid e_T^*, s_T]}{\partial e_T} \right)^2 & 2h_T \cdot e_T^* \cdot \left(\frac{\partial \text{Var}[W \mid e_T^*, s_T]}{\partial e_T} \right) \\ 2h_T \cdot e_T^* \cdot \left(\frac{\partial \text{Var}[W \mid e_T^*, s_T]}{\partial e_T} \right) & (2h_T \cdot e_T^*)^2 \end{pmatrix} \right]^{-1} E \left[\begin{pmatrix} \frac{\partial \text{Var}[W \mid e_T^*, s_T]}{\partial e_T} \cdot \frac{\partial E[W \mid e_T^*, s_T]}{\partial e_T} \\ 2h_T \cdot e_T^* \cdot \frac{\partial E[W \mid e_T^*, s_T]}{\partial e_T} \end{pmatrix} \right].
\end{aligned}$$

Hence, γ and θ are identified.

Given that θ and V_T are identified, one can obtain the following via Equation (8):

$$\eta = 2\theta \cdot E[h_{T-1} e_{T-1}^*] \cdot E \left[\frac{\partial E[V(e_T^*, s_T \mid e_{T-1}^*, s_{T-1})]}{\partial e_{T-1}} \right]^{-1},$$

which uses the assumption that $E \left[\frac{\partial E[V(e_T^*, s_T \mid e_{T-1}^*, s_{T-1})]}{\partial e_{T-1}} \right] \neq 0$.

Viewing Equation (10) as a function of δ , define

$$\pi(\delta) = \eta\delta \cdot \frac{\partial E[E[V(e_T^*, s_T \mid \tilde{e}_{T-1}, s_{T-1}) \mid e_{T-2}^*, s_{T-2}]]}{\partial e_{T-2}} - \eta\theta \cdot \frac{\partial E[h_{T-1} \cdot \tilde{e}_{T-1}^2 \mid e_{T-2}^*, s_{T-2}]]}{\partial e_{T-2}} - 2\theta \cdot h_{T-2} \cdot e_{T-2}^*.$$

Then, the true value of δ satisfies $\pi(\delta) = 0$. For the remainder of the proof, it suffices to show that the rank condition is satisfied—i.e., $\partial\pi(\delta) / \partial\delta \neq 0$.

Because \tilde{e}_{T-1} solves the maximization problem with respect to \tilde{V}_{T-1} , it satisfies the first-order condition in Equation (9). By the envelope theorem,

$$\delta \cdot \frac{\partial^2 E[E[V(e_T^*, s_T \mid \tilde{e}_{T-1}, s_{T-1}) \mid e_{T-2}^*, s_{T-2}]]}{\partial e_{T-2} \partial \delta} - \eta\theta \cdot \frac{\partial^2 E[h_{T-1} \cdot \tilde{e}_{T-1}^2 \mid e_{T-2}^*, s_{T-2}]]}{\partial e_{T-2} \partial \delta} = 0.$$

Therefore,

$$\frac{\partial\pi(\delta)}{\partial\delta} = \eta \cdot \frac{\partial E[E[V(e_T^*, s_T \mid \tilde{e}_{T-1}, s_{T-1}) \mid e_{T-2}^*, s_{T-2}]]}{\partial e_{T-2}}.$$

By Assumption 2, the rank condition is satisfied and, thus, δ is identified.

(Q.E.D.)

Proof of Proposition 3. The proof proceeds in two steps. In the first step, we show that the time-dependence parameters are identified without restrictions if the time-preference parameters β and δ are given. In the second step, the parameters β and δ are determined under Assumption 3.

Step 1. Let β and δ be given. At time T , the disutility θ_T and risk aversion γ are identified per Proposition 2.

At time $T-1$, the maximization condition in Equation (8), with θ replaced by θ_{T-1} , becomes

$$\beta\delta \cdot \frac{\partial E[V(e_T^*, s_T \mid e_{T-1}^*, s_{T-1})]}{\partial e_{T-1}} - 2\theta_{T-1} \cdot h_{T-1} \cdot e_{T-1}^* = 0.$$

With known β , δ , V_T and e_{T-1}^* , θ_{T-1} is identified as a function of β and δ such that

$$\theta_{T-1}(\beta, \delta) = \beta\delta \cdot E \left[\frac{\partial E[V(e_T^*, s_T \mid e_{T-1}^*, s_{T-1})]}{\partial e_{T-1}} \right] \cdot \left(2E[h_{T-1} \cdot e_{T-1}^*] \right)^{-1},$$

given that $E[h_{T-1} \cdot e_{T-1}^*] \neq 0$ —i.e., there exist some agents who exert effort at $T-1$.

At time $T-2$, the maximization condition in Equation (10), with θ replaced by θ_{T-2} , becomes

$$\beta\delta \cdot \frac{\partial E[\tilde{V}(\tilde{e}_{T-1}, s_{T-1} \mid e_{T-2}^*, s_{T-2})]}{\partial e_{T-2}} - 2\theta_{T-2} \cdot h_{T-2} \cdot e_{T-2}^* = 0.$$

Again, θ_{T-1} is identified as a function of β and δ such that

$$\theta_{T-2}(\beta, \delta) = \beta\delta \cdot E \left[\frac{\partial E[\tilde{V}(\tilde{e}_{T-1}, s_{T-1} \mid e_{T-2}^*, s_{T-2})]}{\partial e_{T-2}} \right] \cdot \left(2E[h_{T-2} \cdot e_{T-2}^*] \right)^{-1}.$$

In a similar manner, θ_t is identified as a function of β and δ for $t \leq T-3$ given by

$$\theta_t(\beta, \delta) = \beta\delta \cdot E \left[\frac{\partial E[\tilde{V}(\tilde{e}_{t+1}, s_{t+1} \mid e_t^*, s_t)]}{\partial e_t} \right] \cdot \left(2E[h_t \cdot e_t^*] \right)^{-1}.$$

Hence, the time-dependent disutility $\theta_t = \{\theta_1, \theta_2, \dots, \theta_T\}$ is identified given β and δ .

Step 2. Because we have Θ determined conditional on β and δ , the restrictions on Θ , per Assumption 3(1), can be also represented as a function of β and δ .

$$R^*(\beta, \delta) \equiv R(\Theta(\beta, \delta)).$$

Because the true values of time preference $\Delta = \{\beta, \delta\}$ satisfy the two restrictions, they are identified using the restrictions if the solution is unique. Once β and δ are identified, the identification of the time-dependent disutility parameters follows from the function $\theta_t(\beta, \delta)$.

A sufficient condition for identification is that the restrictions satisfy the full-rank condition with regard to β and δ . That is, the Jacobian matrix

$$\frac{\partial R^*}{\partial(\beta, \delta)} = \begin{pmatrix} \frac{\partial \eta^*}{\partial \beta} & \frac{\partial \eta^*}{\partial \delta} \\ \frac{\partial \eta_2^*}{\partial \beta} & \frac{\partial \eta_2^*}{\partial \delta} \end{pmatrix}$$

has a full rank. By chain rule,

$$\frac{\partial R^*}{\partial(\beta, \delta)} = \frac{\partial R}{\partial \Theta'} \cdot \frac{\partial \Theta}{\partial(\beta, \delta)}.$$

Under the assumption that $\text{rank}(\partial R / \partial \mathbf{T}) = 2$ and $\text{rank}(\partial \mathbf{T} / \partial(\beta, \delta)) = 2$, $\partial R^* / \partial(\beta, \delta)$ has a full rank.

The first assumption that $\text{rank}(\partial R / \partial \mathbf{T}) = 2$ states that the restrictions are linearly independent, which is easy to verify.

To verify the second assumption, observe that

$$\frac{\partial \theta_t}{\partial \delta} = \beta \mathbb{E} \left[\frac{\partial \mathbb{E}[\tilde{V}(\tilde{e}_{t+1}, s_{t+1} \mid e_t^*, s_t)]}{\partial e_t} \right] \cdot \left(2\mathbb{E}[h_t \cdot e_t^*] \right)^{-1} + \beta \delta \left(2\mathbb{E}[h_t \cdot e_t^*] \right)^{-1} \cdot \frac{\partial}{\partial \delta} \left(\mathbb{E} \left[\frac{\partial \mathbb{E}[\tilde{V}(\tilde{e}_{t+1}, s_{t+1} \mid e_t^*, s_t)]}{\partial e_t} \right] \right).$$

Meanwhile,

$$\frac{\partial}{\partial \beta} \left(\mathbb{E} \left[\frac{\partial \mathbb{E}[\tilde{V}(\tilde{e}_{t+1}, s_{t+1} \mid e_t^*, s_t)]}{\partial e_t} \right] \right) = 0$$

because \tilde{V}_{t+1} is not dependent on the present-bias factor by construction. Therefore,

$$\frac{\partial \theta_t}{\partial \beta} = \delta \mathbb{E} \left[\frac{\partial \mathbb{E}[\tilde{V}(\tilde{e}_{t+1}, s_{t+1} \mid e_t^*, s_t)]}{\partial e_t} \right] \cdot \left(2\mathbb{E}[h_t \cdot e_t^*] \right)^{-1}.$$

The rank condition requires $\partial \Theta / \partial \delta$ and $\partial \Theta / \partial \beta$ to be linearly independent, which is satisfied if

$\partial \left(\mathbb{E} \left[\frac{\partial \mathbb{E}[\tilde{V}(\tilde{e}_{t+1}, s_{t+1} \mid e_t^*, s_t)]}{\partial e_t} \right] \right) / \partial \delta \neq 0$. Hence, β and δ are identified.

(Q.E.D.)

Proof of Proposition 4. We first show that θ_B , θ_M , and θ_E are identified assuming that T_0 and T_1 are given. Subsequently, we discuss identification of T_0 and T_1 .

Given T_0 and T_1 , the restrictions, as discussed in Assumption 3(1), are represented as

$$R(\Theta) = \begin{pmatrix} \theta_1 - \theta_2 \\ \theta_1 - \theta_3 \\ \vdots \\ \theta_1 - \theta_{T_0} \\ \theta_{T_0+1} - \theta_{T_0+2} \\ \vdots \\ \theta_{T_0+1} - \theta_{T_1-1} \\ \theta_{T_1} - \theta_{T_1+1} \\ \vdots \\ \theta_{T_1} - \theta_T \end{pmatrix}.$$

One can show that the rank of $\partial R/\partial \Theta'$ is $T-3$, and, thus, Assumption 3(1) is satisfied if $T \geq 5$.

If T is strictly greater than 5, there are extra restrictions available. Hence, the extra restrictions can be used to determine T_0 and T_1 if they are unknowns. Regardless of T_0 and T_1 , the assumption that each period contains at least two days implies that $\theta_1 = \theta_2$ and $\theta_T = \theta_{T-1}$. Because the two restrictions are sufficient to identify the general time-dependence structure in θ_t for $t = 2, 3, \dots, T-1$, one can determine the point at which the disutility parameters exhibit discontinuities. Such discontinuities identify T_0 and T_1 .

(Q.E.D.)

B. Identification of General Infinite-Horizon Model

This part of the appendix provides identification arguments for a general model that includes terminal actions (i.e., agents' stay/leave decision). Incorporating terminal actions naturally leads to an infinite-horizon setting because the agent's decision to leave the firm is permanent, and, thus, the agent's dynamic optimization problem is based on his or her lifetime expected payoffs. The notation follows the main paper unless defined otherwise.

B.1. Utility Function with Stay-or-Leave Decision

Agent i in month m at time t (day) derives utility based on a sequence of actions—whether to stay with the firm (d_{imt}) and, conditional on staying, how much effort to exert (e_{imt}) such that

$$U_{imt} = \begin{cases} u_{imt} + \varepsilon_{imt}, & \text{if } d_{imt} = 1, \\ \bar{u} + \varepsilon_{0imt}, & \text{if } d_{imt} = 0. \end{cases}$$

If the agent decides to stay with the firm ($d_{imt} = 1$), he or she exerts effort (e_{imt}) and receives instantaneous utility

$$u_{imt} = u(e_{imt}, s_{imt}; \Theta) = E[W_{imt} \mid e_{imt}, s_{imt}] - \gamma_i \text{Var}[W_{imt} \mid e_{imt}, s_{imt}] - c(z_{imt}; \Theta) \cdot h_{imt} \cdot e_{imt}^2,$$

as previously defined in **Equation (4)**. Subsequently, the agent's performance is determined by the sales response functions given by **Equations (1) and (2)**. In contrast, if the agent decides to leave the firm ($d_{imt} = 0$), he or she exerts zero effort ($e_{imt} = 0$) and receives reservation utility \bar{u} , which represents the value of the outside option. The decision to leave is an absorbing state (i.e., permanent and irrevocable). More formally, if $d_{imt} = 0$, then $d_{ik\tau} = e_{ik\tau} = 0$ for all $k \geq m$ and $\tau \geq t$.

To accommodate the stay/leave decision, the agent's utility includes a structural error term $\varepsilon_{imt} = (\varepsilon_{0imt}, \varepsilon_{1imt})$, which represents the states unobserved by the researcher but observed by the agent in making the stay-or-leave decision d_{imt} . The structural error is specific to the stay-or-leave decision and, thus, does not depend on the agent's choice of effort.

B.2. Recursive Representation

The agent maximizes the discounted present value of the expected utility stream. Under the quasi-hyperbolic discounting model, the choice-specific value function is represented as the infinite sum of discounted future utilities such that

$$V_{imt} = U_{imt} + \beta E \left[\sum_{\tau=t+1}^{\infty} \delta^{\tau-t} \max_{d_{im\tau}, e_{im\tau}} U_{im\tau} \mid d_{imt}, e_{imt}, s_{imt} \right].$$

Exploiting additive separability of ε_{imt} , let us define $v(d, e, s) = V_{imt} - \varepsilon_{imt}$ as the *choice-specific deterministic value*, which separates out the unobserved utility ε_{imt} from the value function. Hence, if the agent chooses to stay with the firm, then

$$v(d_{imt} = 1, e_{imt}, s_{imt}) = u_{imt} + \beta \mathbb{E} \left[\sum_{\tau=t+1}^{\infty} \delta^{\tau-t} \max_{d_{im\tau}, e_{im\tau}} U_{im\tau} \mid d_{imt} = 1, e_{imt}, s_{imt} \right].$$

In contrast, if the agent chooses to leave the firm, the absorbing state implies that the agent's choice-specific deterministic value degenerates to a constant. Denote this constant as ρ such that

$$v(d_{imt} = 0, e_{imt} = 0, s_{imt}) = \rho.$$

The agent's dynamic problem can be represented by a recursive system with two value functions:

$$v(d, e, s) = \begin{cases} u(e, s; \Theta) + \beta \delta \mathbb{E} \left[\max_{d', e'} \tilde{v}(d', e', s') + \varepsilon_d' \mid d = 1, e, s \right], & \text{if } d = 1, \\ \rho, & \text{if } d = 0, \end{cases} \quad (\text{B.1})$$

where

$$\tilde{v}(d, e, s) = \begin{cases} u(e, s; \Theta) + \delta \mathbb{E} \left[\max_{d', e'} \tilde{v}(d', e', s') + \varepsilon_d' \mid d = 1, e, s \right], & \text{if } d = 1, \\ \rho, & \text{if } d = 0. \end{cases} \quad (\text{B.2})$$

In the above equations, the prime ($'$) symbol represents the subsequent period for the respective variable. Due to the time inconsistency caused by the quasi-hyperbolic discounting, the recursive form requires an additional nuisance value function for the future maximization problem, similar to **Equations (5) and (6)** in the main paper.

B.3. Identification

The identification arguments proceed in two steps: first, the choice-specific deterministic values between stay vs. leave are identified from the conditional choice probabilities; and, second, the structural parameters of utility functions are parametrically identified by showing how the rank conditions are satisfied.

Because the structure of the sales response function is identical to that in the main paper, Proposition 1 holds under the infinite-horizon setting. Hence, by Proposition 1, the agent's optimal effort, conditional on staying with the firm, is identified as a function of the state variables.

B.3.1. Value Function and Time Preference. The agent's decision of whether to stay with the firm is made by the following rule:

$$d_{imt} = \begin{cases} 1, & \text{if } \rho + \varepsilon_0 \leq v(1, e, s) + \varepsilon_1, \\ 0, & \text{if } \rho + \varepsilon_0 > v(1, e, s) + \varepsilon_1. \end{cases}$$

Assumption B.1. *The unobserved utilities ε_{1imt} and ε_{0imt} are independently drawn from a Type-I extreme value distribution with location parameter zero and scale parameter σ_ε and are independently and identically distributed across agents and over time.*

Proposition B.1. *Under Assumption B.1, the difference in choice-specific deterministic values scaled by σ_ε , $(v(1, e, s) - \rho) / \sigma_\varepsilon$, is nonparametrically identified.*

*Proof.*¹⁷ Conditional on the state variable s , the probability of staying with the firm is given by

$$\begin{aligned} \Pr(d = 1 \mid s) &= \Pr(v(1, e, s) + \varepsilon_1 \geq \rho + \varepsilon_0) \\ &= \Pr\left(\frac{\varepsilon_0 - \varepsilon_1}{\sigma_\varepsilon} \leq \frac{v(1, e, s) - \rho}{\sigma_\varepsilon}\right) \\ &= F\left(\frac{v(1, e, s) - \rho}{\sigma_\varepsilon}\right), \end{aligned}$$

where F is the cumulative distribution function of $(\varepsilon_0 - \varepsilon_1) / \sigma_\varepsilon$. By Assumption B.1, F is known. The conditional probability $\Pr(d = 1 \mid s)$ is identified from the data. Thus, the difference in the choice-specific value function scaled by σ_ε is identified by

$$\frac{v(1, e, s) - \rho}{\sigma_\varepsilon} = F^{-1}[\Pr(d = 1 \mid s)]. \quad (\text{Q.E.D.})$$

Although the value function v is identified up to location and scale, the identification of the nuisance value function \tilde{v} is not straightforward. For identification, we make use of the model feature in which \tilde{v} cancels out in the system of equations by expressing \tilde{v} in terms of v and the primitives. Multiplying **Equation (B.2)** by β and then subtracting it from **Equation (B.1)** yields

$$\tilde{v}(1, e, s) = \frac{\beta - 1}{\beta} u(e, s; \Theta) + \frac{1}{\beta} v(1, e, s).$$

Substituting this back into **Equation (B.1)** leads to

$$v(1, e, s) = u(e, s; \Theta) + \delta \mathbb{E}\left[\max\{(\beta - 1)u(e', s'; \Theta) + v(1, e', s') + \beta\varepsilon_1', \rho + \beta\varepsilon_0\} \mid d = 1, e, s\right]. \quad (\text{B.3})$$

Equation (B.3) is the key identifying equation for a general infinite-horizon model. If the exponential discounting model is used, then $\beta = 1$, and, thus, the subsequent period utility function $u(e', s'; \Theta)$ is

¹⁷ The proof builds upon the arguments in Magnac and Thesmar (2002).

canceled out inside **Equation (B.3)**. Hence, from the identification results in Magnac and Thesmar (2002), the utility function is nonparametrically identified, given that there exist some variables satisfying the exclusion restrictions.

However, under the hyperbolic discounting model, $\beta \neq 1$, and the identification argument does not directly apply because the expected future value depends on the unknown instantaneous utility function in **Equation (B.3)**. More specifically, the maximization and expectation operators taken on the unknown function create an ill-posed problem, and, as a result, it is difficult, if not impossible, to nonparametrically identify the utility function. Hence, following Chung et al. (2021a), we exploit parameterization of the instantaneous utility function to facilitate identification. Under the parametric specification (given by **Equation (4)**), the instantaneous utility function u is known up to a finite-dimensional set of parameters. Let μ be the vector of the structural parameters $\mu = (\beta, \delta, \rho, \sigma_\varepsilon, \Theta)$. Also let $\psi(s) = (v(1, e, s) - \rho) / \sigma_\varepsilon$, which was previously identified by Proposition B.1.

Subtract ρ from both sides of **Equation (B.3)** to obtain

$$\sigma_\varepsilon \psi(s) = u(e, s; \Theta) - \rho + \delta E \left[\max \{ (\beta - 1)u(e', s'; \Theta) + \sigma_\varepsilon \psi(s') + \rho + \beta \varepsilon_1', \rho + \beta \varepsilon_0' \} \mid d = 1, e, s \right].$$

By the extreme value distribution assumption for ε , we can compute the expectation of the maximum conditional on the state variable as

$$\begin{aligned} \Lambda(s' \mid \mu) &\equiv E \left[\max \{ (\beta - 1)u(e', s' \mid \Theta) + \sigma_\varepsilon \psi(s') + \rho + \beta \varepsilon_1', \rho + \beta \varepsilon_0' \} \mid s' \right] \\ &= \beta \sigma_\varepsilon \ln \left[\exp \left\{ \frac{(\beta - 1)u(e', s' \mid \Theta) + \sigma_\varepsilon \psi(s') + \rho}{\beta \sigma_\varepsilon} \right\} + \exp \left\{ \frac{\rho}{\beta \sigma_\varepsilon} \right\} \mid s' \right]. \end{aligned}$$

Thus, the expected future utility in the value function can be written as

$$E \left[\max \{ (\beta - 1)u(e', s' \mid \Theta) + \sigma_\varepsilon \psi(s') + \rho + \beta \varepsilon_1', \rho + \beta \varepsilon_0' \} \mid d = 1, e, s \right] = \int \Lambda(s' \mid \mu) f(s' \mid e, s) ds',$$

where $f(s' \mid e, s)$ is the probability density function of s' conditional on $d = 1$ and (e, s) .

Define

$$\Pi(\mu \mid s) = u(e, s \mid \Theta) - \sigma_\varepsilon \psi(s) - \rho + \delta \int \Lambda(s' \mid \mu) f(s' \mid e, s) ds'.$$

Then, the parameters that satisfy **Equation (B.3)** also satisfy $\Pi(\mu \mid s) = 0$. Hence, the solution to $\Pi(\mu \mid s) = 0$ is the true parameters, provided that the solution is unique. A sufficient condition for the uniqueness of the solution to this problem is the rank condition.

Assumption B.2. (Rank Condition). *There exists a subset $\{s_j : j = 1, 2, \dots, J\}$ in the support of s such that the matrix $\{\partial \Pi(\mu | s_j) / \partial \mu : j = 1, 2, \dots, J\}$ has a rank greater than or equal to the dimension of μ .*

Proposition B.2. *Under Assumptions B.1 and B.2, the parameter vector $\mu = (\beta, \delta, \rho, \sigma_\varepsilon, \Theta)$ is identified.*

B.3.2. Time Dependence. Let time dependence be fully flexible, allowing the disutility parameters to depend on time t in an arbitrary fashion such that

$$c(z_{int}, \Theta) = \tau_t.$$

Under this specification, we derive the rank condition for identification. Some algebra, using the $\Pi(\mu | s)$ expression defined above, yields

$$\begin{aligned} \frac{\partial \Pi}{\partial \beta} &= -\frac{\delta \rho}{\beta} - \frac{\delta}{\beta} \int \Lambda(s' | \mu) f(s' | e, s) ds' + \frac{\delta}{\beta} \int \eta(s' | \mu) \cdot [u(e', s'; \Theta) - \sigma_\varepsilon \psi(s')] f(s' | e, s) ds', \\ \frac{\partial \Pi}{\partial \delta} &= \int \Lambda(s' | \mu) f(s' | e, s) ds', \\ \frac{\partial \Pi}{\partial \rho} &= -1 + \delta, \\ \frac{\partial \Pi}{\partial \sigma_\varepsilon} &= -\frac{\delta \rho}{\sigma} - \psi(s) + \frac{\delta(1 - \beta)}{\sigma} \int \eta(s' | \mu) \cdot u(e', s'; \Theta) f(s' | e, s) ds', \\ \frac{\partial \Pi}{\partial \gamma} &= -\text{Var}[W | e, s] + \delta(1 - \beta) \int \eta(s' | \mu) \cdot \text{Var}[W | e, s] f(s' | e, s) ds', \\ \frac{\partial \Pi}{\partial \tau_t} &= z_t \cdot h \cdot e^2 + \delta(1 - \beta) \int \eta(s' | \mu) \cdot z'_t \cdot h' \cdot (e')^2 f(s' | e, s) ds', \end{aligned}$$

where z_t is the dummy variable for the t -th day of a month and

$$\eta(s | \mu) = \frac{\exp[(\beta - 1)u(e, s; \Theta) + \sigma_\varepsilon \psi(s) + \rho] / \beta \sigma_\varepsilon}{\exp[(\beta - 1)u(e, s; \Theta) + \sigma_\varepsilon \psi(s) + \rho] / \beta \sigma_\varepsilon + \exp[\rho / \beta \sigma_\varepsilon]}.$$

Here, we focus on the derivative with respect to τ_t for its relevance. The first term is the effect of τ_t on the instantaneous utility, and the second term captures the effect on the expected future value. They must be linearly independent to satisfy Assumption B.2. The sufficient conditions for the rank condition are

Condition B.1. The conditional distribution of s' given (e, s) is complete for any value of s .

Condition B.2. The values $\psi(s)$, $\text{Var}[W | e, s]$ and $z_t \cdot h \cdot e^2$ for $t = 1, 2, \dots, T$ are linearly independent and not constant functions of s .

Condition B.1 is a completeness assumption that is often used for identification. A distribution $f(x)$ is said to be complete if $\int g(x)f(x)dx = 0$ holds only when $g(x) = 0$. If $f(x | y)$ is complete for all y , linear

independence of two functions, $g_1(x)$ and $g_2(x)$, translates into linear independence of $\int g_1(x)f(x|y)dx$ and $\int g_2(x)f(x|y)dx$. The completeness assumption is satisfied if the distribution belongs to the exponential family of distributions. For instance, the log-normal distribution of the sales shock, used in the paper's empirical setting, readily satisfies the completeness assumption.

Condition B.2 is a linear independence assumption on functions that are identified (up to scale) without the knowledge of μ . By construction, $\{z_t \cdot h \cdot e^2 : t = 1, 2, \dots, T\}$ are linearly independent as long as $h \cdot e^2 > 0$ for some observations in each day t . If Condition B.2 holds, one can show that $\Lambda(s|\mu)$ and $\eta(s|\mu)$ are also linearly independent using their specific functional forms. Thus, combining Conditions B.1 and B.2, we obtain the rank condition for identification.

We further note that, different from Proposition 3 in the main paper, time preference Δ and time dependence Θ are identified *without any dimension reduction* imposed under the infinite-horizon setting. The difference stems from how the identifying equation is obtained. In the finite-horizon model, the identifying equation is derived from the agent's dynamic choice of effort for each day. The optimal effort is chosen to balance the trade-off between present disutility (associated with time dependence) and expected future utility (associated with time preference). The intertemporal optimization provides the ratio between the two parameters but does not provide scale normalization. Consequently, two restrictions are needed to pin down the scale of the parameters.

The identifying equation in the infinite-horizon model, in contrast, is derived from the agent's stay/leave decision, as discussed in Proposition B.1. It is not an intertemporal optimization, but a static choice between stay and leave. The value of leaving the firm does not depend on time preference or dependence and, thus, provides a time-constant normalization to the model. The distributional assumption on the unobserved utilities associated with the stay/leave decision helps identify the value function. Although the value function itself is identified only up to location (ρ) and scale (σ_ε), time preference and dependence are identified because they have linearly independent variations of the location and scale parameters. Thus, as long as the rank condition holds, no more restrictions are needed for location and scale normalization.